THE ROLE OF TRADITIONAL EXCHANGES IN FRAGMENTED MARKETS
- AN EMPIRICAL ANALYSIS POST MIFID -

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Vorwort

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Contents

List of Figures

List of Tables

Chapter 1

Introduction

"MiFID has changed European capital markets in many ways. It has brought greater competition between trading venues and between investment firms both on trading costs and execution services. It has also contributed to substantial investments in technology for trading and platforms. [...] Still, there is scope to bring more clarity to some definitions and further harmonise rules and supervisory practices. In other areas, such as market quality (price formation) and integrity, the impact of the Directive is not yet apparent, since evidence remains fairly controversial and inconclusive."

Centre of European Policy Studies (2011)

Chapter Overview. In this chapter, I introduce the main ideas that motivate this thesis. In particular, Section 1.1 briefly wraps up the most important points with regard to background and motivation. Section 1.2 presents my research questions and Section 1.3 gives an overview of the remaining structure.

1.1 Motivation

THE introduction of the European Markets in Financial Instruments Directive (MiFID) on November 1, 2007, has significantly altered European equity markets. MiFID is part of the European *Financial Services Action Plan* (FSAP) and replaced the *Investment Services Directive* (ISD) which was established in 1993.[1] The overall goal of MiFID is to establish fair, transparent, and efficient equity trading in Europe. Top priority within this goal is investor protection and an improvement of market quality by fostering competition between trading venues. An important step towards increased competition in the context of MiFID was the abolishment of the so-called *Concentration Rule* as well as the proliferation of new alternative trading venues. Before MiFID, the Concentration Rule systematically favored traditional exchanges, as for instance the London Stock Exchange (LSE) or Deutsche Boerse and thus created high market entrance barriers for new trading venues. For example, the concentration rule forced investment firms to route particular orders, such as orders of retail investors, to a regulated exchange.

After November 2007, MiFID allows different types of trading venues to compete for order flow in European equity markets. As a consequence, order flow and liquidity become fragmented across various trading venues.[2] Besides traditional regulated exchanges, the Directive distinguishes between so-called *Multilateral Trading Facilities (MTFs)*, such as Chi-X, BATS, or Turquoise, and systematic internalizers (SI), such as Goldman Sachs International.[3] MiFID defines traditional exchanges as regulated markets where market prices are formed by matching a multitude of buys and sells according to a specific set of trading rules. MTFs are defined similar, but MTFs do not provide particular services which have to be covered by traditional exchanges.[4] There

[1] MiFID consists of a framework Directive (Directive 2004/39/EC), an Implementing Directive (Directive 2006/73/EC), and an Implementing Regulation (Regulation No. 1287/2006). It was also adopted by Iceland, Liechtenstein, and Norway. Section 2.1 in Chapter 2 gives a detailed overview of MiFID.

[2] See `http://mifiddatabase.esma.europa.eu/` for a complete list of all MTFs, SIs, and regulated markets operating in the EU (European Union).

[3] Due to data availability, this thesis covers the year 2009 when BATS and Chi-X were still competitors. In November 2011, BATS Europe acquired Chi-X and combined the trading venues.

[4] This thesis focuses on the competition between traditional exchanges and MTFs. Therefore, I do not discuss SI's in detail. For further information about SI's please see, European Commission (2010).

is for instance no listing process at MTFs and they are also not capable of changing the regulatory framework for particular asset classes or single stocks, meaning a change in trading rules or changes in listing requirements. Besides other factors, these are reasons for MTFs having a relative cost advantage compared to traditional exchanges.

Once MTFs entered the market, they complied with heterogeneous desires of different trading clientele, such as trading speed, anonymity, or innovative fee schedules which quickly lead to the fragmentation of order flow and liquidity. Intuitively, the probability of order execution should decrease if demand and supply are separated across various platforms. Especially theoretical works of market microstructure point to this problem. Pagano (1989a), Pagano (1989b), and Chowdhry and Nanda (1991) study the effect of so-called network externalities, i.e., liquidity spirals. Their findings suggest that order flow should concentrate on a single platform to increase the probability of order execution. At the same time, liquidity on this platform increases even more through positive network externalities, because other market participants route new orders to the trading platform with the relatively highest level of liquidity and therefore order execution. Theoretical findings of market microstructure thus contradict the idea and objectives of MiFID because it does not – unlike US regulation – enforce price-time priority across different markets.[5]

In this regard, MiFID builds upon the self-regulation forces of the market itself. The regulators argue that increased inter-market competition may reduce the quasi-monopoly power of traditional exchanges and thus decrease transaction costs and inspire trading venues to develop new services (European Commission, 2010). As a result, European equity trading has become more fragmented since the introduction of MiFID. Market statistics underline this development accordingly.[6] Within the fragmented European trading landscape, UK blue chip stocks are the most fragmented equities. For example, LSE's market share in FTSE 100 constituents decreased continuously from close to 100% in 2007 to just 43% in June 2011.[7]

[5] In the US, equity markets are electronically linked by technology via the *Inter-market Trading System (ITS)* and private low latency communication linkages.The *Regulation National Market System (RegNMS)* specifically forces trading venues to execute orders by the best available price (RegNMS, Rule 611(1)).

[6] See Figures 2.1 and 2.2.

[7] For detailed statistics on European equity market fragmentation, see `http://fragmentation.`

One motivation for this thesis stems from the obvious contradiction between market microstructure theory and MiFID's goals to increase competition and thus fragmentation in the European equity trading. Another major motivation is connected to a more practical issue. The – de facto – continuously increasing competitive pressure on traditional exchanges from alternative trading platforms such as MTFs, raises questions about the contribution of different trading platforms to overall market efficiency. Due to technological progress, the market environment for equity trading has changed tremendously over the past years. This fact also leads to new scientific questions, especially with regard to geographical centralization of liquidity and order flow. The new, MiFID induced competition leads to a fragmentation of order flow and liquidity in European equity markets. Yet, potential negative effects of market fragmentation may today be alleviated by modern information and communication technology where various trading venues can virtually be integrated. Investors may for instance use Smart Order Routing (SOR) technologies which guarantee best execution across trading venues within milliseconds (Foucault and Menkveld (2008)). Nevertheless, having a multitude of trading venues which are virtually connected still leaves the question whether individual trading venues actually contribute to overall market quality and efficiency.

Therefore, this thesis strives to analyze the newly evolved competition between traditional exchanges and MTFs in the aftermath of MiFID. One major focus herein is the influence of the continuously increasing market fragmentation on trading intensity and market quality. To address this question, I focus on the UK equity market which exhibits the largest degree of fragmentation within Europe. In empirical analyses, I compare order book data of the LSE and the three largest European MTFs – Chi-X, BATS, and Turquoise – in 2009. The availability of this data allows me not only to analyze the influence of market fragmentation on market quality, but also to address competition between these trading venues. To identify potential changes, I compare the role which these trading venues play in a fragmented market environment in an (a) intraday analysis and (b) over time. I compare different time periods and trading circumstances which may influence market participants' choice of a trading venue. Another important as-

fidessa.com.

pect of my thesis is the influence of different market participants on trading venues, trading intensity, and market quality. Regarding market participants, it is important to note that algorithmic and high-frequency trading (HFT) participants have gained large influence in recent years. Due to the particular focus on low latency and innovative fee structures on MTFs, the share of those "modern" market participants is thought to be higher on MTFs compared to traditional exchanges. Consequently, I also consider the influence of these modern market participants on the trading venues.

1.2 Research Outline

The focus of my thesis is to analyze the effects of regulatory changes in the European trading landscape. I particularly concentrate on the influence of order flow fragmentation and competition among trading venues on overall market quality after the introduction of MiFID in November 2007. Market quality, i. e. , the capability of a market to match buy and sell orders, plays a crucial role in capital allocation and is thus of major importance for the economy as a whole. Yet, it is not possible to define market quality by only one single measure. Liquidity probably plays the most important role for market quality because it indicates where market participants prefer to route their orders to. Empirical market microstructure literature offers a large variety of different market quality measures which also include several liquidity measures. The availability of tick-size trade and quote data allows me to apply various of these measures – liquidity and other measures – to investigate my first research question:

Research Question 1: Does increased fragmentation and thus increased competition among trading venues improve overall market quality under MiFID?

My goal is to identify potential changes in market quality on the four largest UK trading venues – according to trading volume – over 2009. My data set covers on a millisecond basis all changes up to the third level of the order book on each of the four trading venues: LSE, Chi-X, BATS, and Turquoise. The overall size of my data set sums up to approximately 2.71 billion data points. To study the impact of increased market fragmentation on market quality, I measure liquidity and several other market quality measures on each trading venue and compare these measures over time. My idea is to compare two periods which exhibit considerably different levels of market fragmentation. Consequently, I compare two different quarters (Q1 and Q4) of 2009.

However, I am not only interested in the influence of market fragmentation on market quality and competition over time. For a single trading venue, Admati and Pfleiderer (1988) explain theoretically why trading tends to be concentrated at particular periods within the trading day. In contrast, evidence on intraday trading patterns in more than one market are very scarce. Only few scholars, as for instance Werner and Kleidon (1996), compare intraday trading patterns in a two-market scenario. On the basis of multiple fragmented European trading landscape, I formulate my second research question:

Research Question 2: How are order flow and liquidity connected during the trading day in a multiple fragmented market environment? Does one market dominate others in specific periods of trading?

To analyze this research question, I calculate various intraday trading patterns for each trading venue and compare them with one another. To capture the impact of market fragmentation on changes in intraday trading patterns, I calculate the patterns for Q1 and Q4 of 2009. This allows me to study changes in intraday patterns over time. I address research questions 1 and 2 in my empirical analysis in Chapter 5.

Additionally, I am not only interested to compare market quality on MTFs and traditional exchanges, but to further address the question how specific types of market participants act in the fragmented trading landscape. The proliferation of electronic equity trading has spurred technological developments which lead to a continuous increase of trading speed and thus to a new category of market participants. In today's equity markets, algorithmic and high-frequency traders account for a large share in daily trading volume.[8] Competition between traditional exchanges and MTFs in combination with the new high-frequency trading clientele that emerged along with MTFs are a second main focus of my thesis. I attempt to identify the behavior of these new market participants in particular market situations and thus their impact on market quality on the LSE, Chi-X, BATS, and Turquoise.

The literature attributes many positive effects to the appearance of MTFs and HFT. Several scholars argue for instance, that increased competition from alternative trad-

[8]See `http://hft.thomsonreuters.com/` for details on HFT trading volume in European markets. The Securities and Exchange Commission (SEC) refers to HFT as «*[...] professional traders acting in a proprietary capacity that engage in strategies that generate a large number of trades on a daily basis [...] characteristics often attributed to proprietary firms engaged in HFT are [...] the use of extraordinarily high-speed and sophisticated computer programs for generating, routing, and executing orders [...] very short time-frames for establishing and liquidating positions [...] ending the trading day in as close to a flat position as possible*» (U.S. Securities & Exchange Commission, 2010, p. 45).

ing platforms on regulated markets leads to an overall increase in market quality (e.g., O'Hara and Ye, 2011). Other academic studies contradict the wide spread argument of practitioners that MTFs would free-ride on traditional exchanges price formation. Contrarily, they find that MTFs often lead in price discovery and information based trading (e.g., Hoffmann, 2010; Riordan et al., 2011; Jung and Katzschner, 2012). Other scholars attribute market maker qualities to HFT. They find that HFT is particularly active on MTFs where they act as new multi-venue market makers (Menkveld, 2011b; Kirilenko et al., 2011).

Yet, these arguments lead to new questions about the competitive relationship of traditional exchanges and MTFs, especially when looking at the HFT trading clientele. Even if both type of trading venues – regulated markets and MTFs – may undergo similar regulatory requirements, the trading clientele on these venues is much more flexible with regard to regulation. HFTs may for instance act as market makers but they are not obliged to follow the regulatory requirements such as traditional market makers, i. e. , liquidity provision according to the rule book of a traditional exchange. Also regulators point out concerns that liquidity provision by HFT may not be granted as stable over time *«[. . .] But unlike an OTC market maker, a proprietary firm typically does not trade directly with customers. The proprietary firm therefore may not have ongoing relationships with customers that can pressure the proprietary trader to provide liquidity in tough trading conditions or less actively traded stocks[. . .]»* (U.S. Securities & Exchange Commission, 2010, p. 50). But not only the trading behavior of HFT may effect the competitive environment of regulated markets and MTFs. Also traditional supplementary functions and services of regulated markets (e.g., circuit breakers or market surveillance) may attract order flow of market participants especially in certain market situations. Therefore, the second empirical part of my thesis concentrates on the following research questions:

Research Question 3: How do different market conditions influence the order routing behavior of market participants in a fragmented market environment?

Research Question 4: What is the influence of market participants' order routing behavior on market quality?

Many papers, which are related to my thesis, measure the effect of fragmentation on market quality over time periods that predominantly reflect normal trading conditions. Therefore, I deliberately investigate abnormal market conditions, i. e. , high price uncertainty or increased inventory risk, with regard to research questions 3 and 4. I also concentrate on the competitive environment of the LSE and the three MTFs when price uncertainty is high and when market conditions are unfavorable for market making. I analyze the contribution to price discovery of each platform in such market conditions because it is an essential aspect of a high-quality market structure to withstand such periods of serious distress and price uncertainty.

1.3 Structure of the Thesis

This thesis consists of seven chapters. The remainder of this thesis is structured as follows. Chapter 2 provides details about the European financial market regulation history as well as a brief outlook on upcoming regulatory changes. I particularly address the creation and implementation process of MiFID, which has lead to increased market fragmentation of European equity markets. This chapter also points out details about the U.K. equity trading landscape and its development in recent history. I address different market structures, major developments at the LSE, and developments with regard to MTFs. Chapter 3 describes theoretical and empirical work, which is closely related to this thesis. I concentrate on three areas of market microstructure: First, the literature addressing competition in fragmented markets, second the literature about intraday trading patterns of market quality measures, and third, the literature addressing the influence of financial market innovation on market fragmentation. Chapter 4 outlines data selection and data processing as well as the employed methodology. Chapters 5 and 6 represent the main research chapters of my thesis.[9] Chapter 5 examines the influence of increasing fragmentation on market quality and intraday trading patterns over 2009. Chapter 6 focuses on the order routing behavior of market participants in a fragmented market environment. I particularly focus on competition and price discovery during abnormal market conditions. Chapter 7 summarizes and concludes the thesis. It also provides an outlook which addresses future research areas.

[9]Both Chapters are based on the joined working papers *"Intraday Trading Patterns in Fragmented Markets - A Post MiFID Analysis"* and *"The Role of Traditional Exchanges in Fragmented Markets"*, with Hans-Peter Burghof and Martin Wagener. The results of these joint working papers have been presented at

- The 15th Annual Conference of the Swiss Society for Financial Market Research, SGF (Zurich, Switzerland).
- The 51st Annual Meeting of the Southwestern Finance Association (New Orleans, USA).
- The 61st Annual Meeting of the Midwest Finance Association (New Orleans, USA).

The results of these joint working papers have also been accepted at

- The 48th Annual Meeting of the Eastern Finance Association (Boston, USA).

Chapter 2

Foundations

"The aim of securities market regulation is to ensure proper disclosure and enforcement via a complex set of intermediaries and institutions. This is achieved not only via legislation, but also by stimulating a process of competition between intermediaries on the basis of reputation and allowing the market to take responsibility for part of the regulatory and enforcement work."

European Investment Bank (2001)

Chapter Overview. This chapter gives a detailed discussion on the Markets in Financial Instruments Directive (MiFID) which became effective on November 1, 2007. MiFID aims to create a level playing field for new alternative trading venues, traditional exchanges, and market participants by the implementation of a single European legislation which holds for all member countries. The main goals are to foster investor protection, competition, and market quality. In a second part, this chapter discusses details about the UK equity market structure and its evolution over time. In particular, I address the development of the LSE as well as the changing landscape in European equity trading due to the emergence of MTFs.

2.1 Markets in Financial Instruments Directive

THE process of matching supply and demand in a financial market that finally cumulates into a price is mainly influenced by two factors. First, market design of trading venues and second the regulatory framework. Both individually influence investor behavior, i.e., their trading strategies, but also competition in financial markets. While market design is to a large extent under the responsibility of a private financial institution which operates the trading venue, the regulatory framework is under public responsibility. For both groups, private and public, it is important to understand that even little changes in the set-up of trading rules or the regulatory environment may have severe implications on the efficiency of a market and thus on economic growth and social welfare. With the introduction of MiFID more than little changes altered the equity market trading landscape across Europe and it is therefore particularly interesting to address the implications of MiFID on the European equity market.

MiFID was adopted by the European Council and the European Parliament on April 21, 2004, and it was implemented in all 27 (now 28) member countries as well as Iceland, Liechtenstein, and Norway on November 1, 2007. As the cornerstone of the European Commission's Financial Services Action Plan, MiFID has the overall objective to foster competition in order to create a fair, transparent, efficient, and integrated European financial market. MiFID provides a regulatory environment that aspires for increasing investor protection and the provision of new services and markets through competition.

Implementation process. The FSAP was initially published in May 1999 and arose from an initiative of the European Council which was held in Cardiff in June 1998. With the introduction of the Euro ahead in January 1999, the European Council *«invited the Commission to table a framework for action [. . .] to improve the single market in financial services»* (European Commission, 1999, p. 3). The FSAP contains 42 articles related to the harmonization of financial services markets within the European Union. It is not only focused on particular sectors of the financial domain, but intends to overcome remaining cross-border barriers within the whole financial service industry through its complementary set of proposed articles. In particular, the FSAP pursuits a single wholesale market, an open and safe financial retail services market, and intelligent rules and supervision (European Commission, 1999). Within the FSAP, MiFID is its most important achievement. It consists of a framework Directive (Directive 2004/39/EC), an Implementing Directive (Directive 2006/73/EC), and an Implementing Regulation (Regulation No 1287/2006) (European Commission, 2010, p. 5).

MiFID replaced the Investment Services Directive (ISD, Council Directive 93/22/EEC) which was introduced in 1993 and implemented in 1995. The ISD was a first step towards harmonization of European financial markets. Its main idea was to deliver a first set of standards to investment firms which provide services or plan to establish branches in member states of the EU, however under a home country's authorization and supervision. Even though the ISD aimed for harmonization it also allowed for market entrance barriers within the financial market. Article 14(3) of the ISD particularly allowed that *«a member state may require that transactions[. . .] be carried out on a regulated market»*. This rule, also know as the Concentration Rule, created a quasi-monopoly position for national exchanges because it required retail orders to be executed on a regulated market only (European Commission, 1993). Davis et al. (2005) show that the Concentration Rule has heavily influenced the development of several European financial markets, e.g., France, Italy, and Spain. Other countries, such as Germany, favored their traditional exchanges by additional regulations such as the *Default Rule*. It contemplated that financial intermediaries execute customer orders on a traditional exchange unless investors explicitly recall an exchange execution (Gomber and Gsell, 2006).

The establishment of these rules indicates that the ISD was not a proper framework to establish a single European market in investment services. National authorities still had the possibility to impose rules and restrict financial services of foreign member state investment firms. Additionally, the scope of investment activities to which the ISD may be applied was too narrow. New products and financial services for all types of investors appeared and grew considerably over time. Yet, the ISD only applied to firms providing *«investment services for third parties on a professional basis»* (European Commission, 1993, Art. 2(1)).

Date	Description
May 1993	Adoption of the ISD (Council Directive 93/22/EEC)
July 1995	ISD comes into effect
June 1998	Cardif European Council invites European Commission to prepare a "framework for action" for a single European financial market
May 1999	European Commission publishes the FSAP
March 2000	European Council agrees on the FSAP in Lisbon
November 2002	European Commission completes draft on the revision of the ISD which from then on becomes MiFID
April 2004	European Parliament approves MiFID framework Directive (Directive 2004/39/EC)
2004 - 2005	Consultation process by CESR
August 2006	European Commission passes the Implementing Directive (Directive 2006/73/EC) and the Implementing Regulation (Regulation No 1287/2006)
November 2007	MiFID comes into full effect in all EU member states

TABLE 2.1: ***Timeline of important steps towards the implementation of MiFID.***

The lack of a single European legislative framework, together with a growing awareness that technology in the financial services sector had developed significantly, led the EU to rethink their financial sector regulation. As a result, MiFID abolished the options for member states to favor their incumbent market when routing orders. It also allowed other types of trading venues to compete for order flow with regulated markets and thus aimed to intensify the harmonization within the European financial market for both professional and retail investors. Table 2.1 gives an overview of the relevant events which are connected to the implementation of MiFID.

The legislative implementation of MiFID follows the *Lamfalussy process* which is named after Baron Lamfalussy, the chairman of the "Committee of Wise Men" that devised the standard legislative implementation process. The Lamfalussy process was proposed in 2001 in order to accelerate the development of European financial services legislation and to enable experts to participate in the legislative process (Lamfalussy et al., 2001). The law-making approach of Lamfalussy contemplates four different levels. Level 1 includes the preparation of a Framework Directive – MiFID itself – which includes guiding principles and requirements. It was adopted by the European Commission and the European Council in April 2004. Level 2 includes measures which deal with details of how MiFID works in practice. For instance, organizational requirements and operating conditions for investment firms which are stated in the Implementing Directive or record-keeping obligations for investment firms, transaction reporting, market transparency measures, and further definitions which are stated in the Implementing Regulation.[1] Those measures were subsequently formulated during the Level 1 implementation by the European Commission with the advice provided by the European Securities Committee. The European Commission released draft versions of both Level 2 documents on February 2006 and passed the Implementing Directive and the Implementing Regulation on August 2006. Level 3 supports these legislative processes and the Committee of European Securities Regulators (CESR) holds an important role in doing so. It assists in a consistent implementation and application of the Level 1 and Level 2 legislative measures across EU Member States by developing recommendations, interpretative guidelines, and common standards. Level 4 deals with the supervision of MiFID and its enforcement. Here, the European Commission controls whether Member States comply with Level 1 and Level 2 legislation and, if appropriate, it becomes active to ensure that the Levels are properly implemented.

MiFID details. Through the implementation of a single legislation within the European Economic Area (EEA), MiFID intends to create a level playing field for investment firms, trading venues, and investors in order to eventually improve market quality. To achieve this goal, MiFID is based on the following three main pillars: *Market Access*, *Transparency*, and *Best Execution*.

1. Market Access: By taking away the option of national authorities to favor their incumbent market via the Concentration Rule, MiFID introduced competition between trading venues. In particular, MiFID allows three trading platforms to compete with one another.

[1] In the context of European legislative instruments, a *Directive* requires its adoption and implementation by each EU Member State before it can have direct effect as a matter of national law and leaves thus some flexibility in the way the Directive is transposed into national law. In contrast to the Directive, a *Regulation* has direct effect in each EU Member State without the need for national-level legislative implementation.

- *Regulated Markets*: A regulated market is specified as *»[...] a multilateral system operated and/or managed by a market operator, which brings together or facilitates the bringing together of multiple third-party buying and selling interests in financial instruments – in the system and in accordance with its non-discretionary rules – in a way that results in a contract, in respect of the financial instruments admitted to trading under its rules and/or systems [...]«* (European Commission Directive, 2004, Article 4(14)). Traditional exchanges, which match buy and sell orders through a limit order book or through dealers, belong to this category. They are liable to a set of transparent and non-discretionary rules and procedures that provide fair and orderly trading.

- *Multilateral Trading Facilities*: A multilateral trading facility is specified as *»[...] a multilateral system, operated by an investment firm or a market operator, which brings together multiple third-party buying and selling interests in financial instruments – in the system and in accordance with non-discretionary rules – in a way that results in a contract [...]«* (European Commission Directive, 2004, Article 4(15)). Within this definition, an *"investment firm"* is defined as *»[...] any legal person whose regular occupation or business is the provision of one or more investment services to third parties and/or the performance of one or more investment activities on a professional basis.«* (European Commission Directive, 2004, Article 4(1)). This definition reveals that MTFs cannot create or change trading rules or listing requirements of asset classes or stocks like a regulated market. However, they may offer trading in stocks which are listed at regulated markets, just like regulated markets.

  MTFs mainly emerged through joint-ventures of large investment firms which used to trade large positions aside of regulated markets even before MiFID.[2] MTFs may thus receive order flow from their owners or founders, which already generates a certain amount of liquidity. However, they should

[2] For instance, Chi-X Europe was established in 2007 by Instinet, a subsidiary of Nomura Holdings and its ownership was eventually broadened to a consortium of major global financial institutions such as BNP Paribas, Citadel, Citigroup, Credit Suisse, Fortis, GETCO Europe Ltd, Goldman Sachs, Merrill Lynch, Morgan Stanley, Optiver, Societe Generale, and UBS.

attract order flow from outside investors in order to grow. To do so, MTFs based their business model on the needs of new types of investors that emerged along with regulatory changes over the past decade: algorithmic and high-frequency traders. By offering low-latency trading infrastructures, innovative fee schedules, and order types, MTFs successfully managed to take away a large bite of market share from regulated markets. Currently, all European blue chip stocks can be traded on MTFs.

- *Systematic Internalizers*: A systematic internalizer is specified as *»[...] an investment firm which, on an organized, frequent and systematic basis, deals on own account by executing client orders outside a regulated market or an MTF«* (European Commission Directive, 2004, Article 4(7)). Large investment firms which match and execute their client orders internally belong to this category of trading venues. However, these trading venues are out of scope in my thesis. I focus on competition between regulated markets and MTFs for several reasons. First and most importantly, both are the main players in the European equity trading landscape. Second, they are fairly similar and hence comparable in terms of MiFID regulatory definitions. And third, they are obliged to the same amount of transparency with regard to quotes and prices. Further discussions are therefore limited to these two types of markets.[3]

2. Transparency: With an increasing number of trading venues, liquidity becomes fragmented and thus does information about available prices, quotes, and order book volumes. Therefore, the "Transparency" pillar is responsible for pre- and post-trade transparency requirements for equity trading on regulated markets and MTFs in order to guarantee a transparent flow of information in the market (European Commission Directive, 2004, Articles (29-30) and (44-45)). Pre-trade transparency rules require trading venues to continuously publish their order books – at least partially – by showing best bid and ask prices together with the volumes of trading interest at these prices. MiFID also allows competent au-

[3]See Gomber and Pierron (2010) for further insights into SI and OTC trading.

thorities, i.e., operators of regulated markets and MTFs, to waive certain pre-trade transparency requirements for shares based on a certain market model or the type and size of certain orders (European Commission Regulation, 2006, Articles (18) and (20)).[4] Particularly, MTFs but also regulated markets have used these waivers to create new services for their clientele, as for instance the execution of trades that are large-in-scale or trades with completely hidden liquidity, known as dark pools.[5] Also new order types such as iceberg orders, where only a part of the order volume is visible in the order book or hidden limit orders are the outcome of these waivers. Post-trade transparency rules include the publication of price, volume and time of all trades that occurred in all listed shares of a trading venue. These post-trade requirements hold also for trades which are executed outside of a regulated market or MTF. However, if trades are of large scale they may be subject to a deferred publication (European Commission Regulation, 2006, Article (28)).

3. Best Execution: The best execution rule sets the framework for investment firms and brokers to execute customer orders. In particular, whenever an intermediary executes a customer order it must *»[...] take all reasonable steps to obtain [...] the best possible result for their clients taking into account price, costs, speed, likelihood of execution and settlement, size, nature or any other consideration relevant to the execution of the order.«* (European Commission Directive, 2004, Article 21(1)). If a client does not give a specific instruction to the investment firm where to execute the order, this broad definition gives investment firms the possibility to decide themselves where to route the order to. However, investment firms have to *»[...] monitor the effectiveness of their order execution arrangements and execution policy in order to identify and, where appropriate, correct any deficiencies. In particular, they shall assess, on a regular basis, whether the execution venues included in the order execution policy provide*

[4]There are four waivers of MiFID pre-trade transparency: *Reference price waiver, negotiated trade waiver, order management facility waiver, and large-in-scale trade waiver.* For details about the individual waivers, see (European Commission Regulation, 2006, Article (18) and (20)).

[5]Generally, dark pools are part of MTFs and follow a price taker model, i.e., within these trading venues large block trades are closed at prices fixed in other trading venues, typically traditional regulated markets. But also regulated markets started to create dark pools to attract additional trading volume. The LSE opened their dark pool unit “Baikal Global Limited” in 2008.

for the best possible result for the client or whether they need to make changes to their execution arrangements.« (European Commission Directive, 2004, Article 21(4)). Additionally, they are required to prove on request that they executed client orders in accordance with this order execution policy (European Commission Directive, 2004, Article 21(5)). Yet, this definition leaves investment firms with the freedom to decide on the number of trading venues they include into their best execution policy and it does not compel investment firms to observe prices at all European trading venues at any possible cost (Gomber and Gsell, 2006). Hence, it is still difficult for investors to properly assess the quality of order execution.

MiFID's aftermath. Since its implementation in November 2007, MiFID has been the cornerstone of Europe's capital markets regulation. Three years after it became applicable the European Commission released a public consultation paper to collect various opinions about MiFID induced changes in European financial markets, as well as ideas for potential improvement of the regulatory framework. The consultation paper addressed all different groups which are affected by MiFID, including professional market participants, investors, national governments, national competent authorities, and academics (European Commission, 2010). The European Commission states that, despite great challenges and negative influences of the financial crisis, MiFID has successfully contributed to increased competition between trading venues and the fostering of innovation within the financial services industry (European Commission, 2010, pp. 5-7). Additionally, transparency requirements and hence investor protection have been significantly improved. Due to greater competition among trading venues, there is evidence that implicit and explicit trading costs have been reduced and trading speed has been accelerated. Investors have now the possibility to benefit from a more integrated European market for financial services because investment firms and trading venues offer their services on a pan-European level (European Commission, 2010, pp. 5-7).

However, not all benefits have reached investors as envisaged since its inception. In an environment where technological progress and macroeconomic events are rapidely changing the level playing field, the regulatory framework needs continuous improvement. To incorporate the lessons-learned from the global financial crisis, new evolving flash-crashes, the extensive use of dark liquidity, the explosively increasing volume of derivatives, and to address further shortcomings of the original directive, the EC started a consultation process which will lead to a second updated version of MiFID – MiFID II – which probably will come into effect in 2015. MiFID II aims to:[6]

- harmonize existing regulatory differences between trading platforms and over-the-counter trading,
- provide an improved regulatory framework for best execution also with regard to other financial instruments, not only stocks,
- and tackle difficulties which emerged through technological developments in trading, i.e., algorithmic and high-frequency trading.

My thesis aims to contribute to this ongoing debate of MiFID II by providing empirical evidence on market quality and market coordination on regulated markets and MTFs. I concentrate on abnormal market conditions which may influence the order routing behavior of market participants and particularly the engagement of HFT market participants.

[6] For a detailed overview of current MiFID II developments, please refer to Ferrarini and Moloney (2012).

2.2 U.K. Equity Trading Landscape

The UK equity market and particularly London have a long lasting tradition as a global financial center and thus they have always been exposed to developments and changes regarding financial markets, no matter whether they were of regulatory or technological nature. Therefore, the UK equity market with its internationally well-known blue chip stock index FTSE 100 is well suited for my analysis. With 29.1% in 2009, the UK equity market exhibited the highest share of equity trading volume within Europe.[7] Even more important is that fact that the FTSE 100 is the most fragmented index within Europe, i.e., trading of its constituents is most scattered across multiple platforms within Europe compared to other indices.[8] The FTSE 100 is an index which stems from a former joint venture between the Financial Times and the LSE. It is an arithmetic value-weighted index that lists the largest 100 companies from the UK according to market capitalization. The index started on January 3, 1984 at the base level of 1000 and reached its highest value (6950.60) to date on December 30, 1999. It is now maintained by the FTSE Group, a subsidiary of the London Stock Exchange Group.[9]

Before I outline particular developments of the UK equity market, it is necessary to address basic trading structures, i.e., the difference between the two major market microstructures: *Dealer markets* vs. *Order-driven markets*.

I. Dealer markets vs. Order-driven markets

Dealer Markets. Dealer markets or also called quote-driven markets were the predominant microstructure of exchange architecture around the world until the mid 1990s. Trading in dealer markets is typically organized by a market maker.[10] He is

[7] Compare Equity Market Report 2009 of the Federation of European Exchanges (FESE), `http://www.fese.eu/`.

[8] For detailed statistics on European equity market fragmentation, see `http://fragmentation.fidessa.com/`.

[9] For further details about the index, see `http://www.ftse.com/`.

[10] Depending on the trading venue, there are quite some synonyms, e.g., dealer, designated sponsor, specialist, quality liquidity provider. However, they all do the same job. In my thesis I stick with the term market maker.

contractually obliged with the stock exchange to quote bid and ask prices up to a certain volume of the universe of stocks which he is registered for. Other market participants are able to buy and sell stocks during the trading day only from him. If a market participant would like to acquire a stock which is currently not in the market maker's inventory, the market maker has the contractual obligation to short sell the stock. For continuously providing liquidity to the market and as a compensation for their inventory risk, market makers earn the difference between quoted bid and ask prices in case of a transaction. Usually, there is a contractual cap for this commission. If a stock exchange allows several market makers to compete for order flow with one another, the competition is mainly based on bid-ask spreads which are then being reduced through competitive forces.[11]

Order-driven Markets. With the introduction of fully electronic trading systems at most major exchanges until the mid 1990s, the advantages of an order-driven market architecture appeared.[12] Today, almost all major exchanges operate their main trading system as a centralized order-driven order book. However, there are many exchanges that combine market maker and order-driven trading and grant market makers additional access to their exchange. Market makers are often responsible for less liquid stocks where a limit-order trading system might be disadvantageous. However, in the presence of many market participants and large trading volumes a limit-order driven market structure may offer several benefits. Here, market participants may act as quasi-market makers and indirectly provide liquidity to the order book. By stating their desire to buy or sell a certain quantity of a stock at a certain price through a limit order, they fill the limit order book and provide liquidity. Yet, market participants using limit orders have to be aware of the execution risk, since their limits may not be reached if the market is moving in the other direction or too many other market participants placed their limits in front of them.[13] From the existing limit orders in the book, market partic-

[11]See Breuer and Burghof (2012) for a detailed literature overview of dealer markets and order-driven markets.

[12]Jain (2005) provides a detailed overview of international exchanges and their switch to fully electronic trading systems.

[13]Usually, order-driven markets have a strict price-time priority for incoming limit orders.

ipants may also choose to buy or sell a stock directly at the best available price by using a market order. The market order is executed immediately, however, it is associated with a price risk depending on the depth of the limit order book where it is executed against. Another benefit of an order-driven market structure is that market participants may observe trading interests of others when looking at the order book and thus get a better feeling of the market.[14] Besides market and limit orders, an order-driven market offers even more types of different orders which market participants may use. Some of them will be outlined more detailed in Subsection III.

II. Major Developments at the LSE

SEAQ. Compared to other large international exchanges, the LSE abandoned its century old tradition of face-to-face dealing with the introduction of electronic trading quite early, along with the deregulatory changes of the *Big Bang* on October 27th, 1986. The main goal of these long awaited UK equity market reforms, known as Big Bang, was to increase competition among market makers and reduce overall execution costs at the LSE. These far-reaching reforms transformed the UK stock market thoroughly (Clemons and Weber, 1990). The whole reform process was mainly influenced by technological change, i.e., the introduction of an open, electronic screen-based quotation system, called the Stock Exchange Automated Quotation system (SEAQ). With this technological progress many of the regulatory relaxations became – at least to a far extent – possible because it considerably eased market surveillance.

Associated with the Big Bang were four major reforms that had a strong influence on the UK equity trading landscape. First, fixed minimum scale broker-dealer commissions were eliminated. Second, an electronic screen-based quotation system was introduced. SEAQ was based on the US exchange system NASDAQ, where market makers could electronically quote their prices (bid and ask) and compete in the system with one another. Market maker's quotes always had to hold for a minimum quantity of stocks for which they were registered. If the quantity that a market maker quotes prices for

[14] Granting order book information usually becomes a business case for trading venues, where market participants pay to receive this superior information.

exceeds the minimum quotation quantity, he was obliged to execute incoming orders up to the quoted amount of stocks. While quotes and competition between market makers were displayed automatically on SEAQ, order execution was still conducted via phone and trades were then reported on SEAQ. Third, dual capacity operations were introduced. Before Big Bang, investment firms could either participate in trading as a broker to manage buys and sells for their clients or as a market maker. On SEAQ, acting in both functions for a single investment firm became legal and most investment firms henceforth operated in the *dual-capacity*. The fourth major reform was to increase competition by opening the exchange for new member firms that could participate in trading (Clemons and Weber, 1990, pp. 44-45).

SETS. In October 1997, the LSE conducted another major market reform and introduced the Stock Exchange Trading System (SETS), which is an order-driven trading system. Initially, SETS was only introduced for its most liquid FTSE 100 constituents, however later, also FTSE 250 constituents were shifted to SETS. The previous dealer-based SEAQ was allowed to continue in parallel. SETS was from now on the official trading system and market makers were now longer obliged to provide bid and ask quotes on the new trading system. Yet, market makers were still allowed to voluntarily provide quotes over the telephone and execute trades off-exchange, i.e., off the SETS order book. The main reason for this technological market development was competitive pressure from all different sides. For instance, other international exchanges tried to gain market share in European equities traded on the LSE. Also alternative electronic trading networks became a serious competition after UK regulation allowed market makers to provide their quotes on such networks. Here, quotes were often better then on the LSE.[15] Also the ISD, as outlined in section 2.1, created additional competitive pressure as it allowed other European automated order matching systems to compete with national exchanges without permission of regulatory authorities in the respective country (ISD, Article 15.4, Council Directive 93/22/EEC).

[15]See Naik and Yadav (1999) for an overview of the effects of the SETS market reform.

TradeElect and further steps. In June 2007, the LSE launched its new electronic trading system *TradElect*. Instead of adapting its existing technology, the LSE replaced its technology completely in order to improve trading speed and market efficiency. This large investment was mainly driven by the latest developments of high-frequency market participants which account for a continuously increasing share in international equity trading. «*[...] The introduction of TradElect, the culmination of a four year investment in next generation technology, will deliver a step change in trading capabilities to the London market. As high-frequency algorithmic traders look globally for pools of liquidity in which to find alpha opportunities, TradElect sets new benchmarks in terms of system capacity and performance[...]*».[16] TradElect enables market participants to execute trades in roughly ten milliseconds, which is a commonly known benchmark for algorithmic trading.

To further improve its competitive position, the LSE took several strategic decisions.[17] A large one was the merger with Borsa Italiana in October 2007. Another large strategic decision was made on December 21, 2009, when the LSE and Turquoise merged parts of their businesses and created a new MTF which offers its services under the name of Turquoise. The dark pool unit of the LSE, known as Baikal Global Limited, was incorporated into Turquoise. The new venture is owned by LSEs' and Turquoises' shareholders, who are mainly global investment banking clients of the LSE.[18] LSE's ownership is now 51% (Gresse, 2011). To cope with increased speed competition from MTFs, the LSE bought MilleniumIT in September 2009. MillenniumIT provides the LSE with a high performance trading technology that allows very low latency order execution.[19]

[16] See London Stock Exchange (2007), `http://www.londonstockexchange.com/about-the-exchange/media-relations/press-releases/2007/londonstockexchangesnewtradingsystemgoeslive.htm`.

[17] See also table 2.2 for an overview of important events at the LSE.

[18] See London Stock Exchange (2009b), `http://www.londonstockexchange.com/about-the-exchange/media-relations/press-releases/2009/londonstockexchangeandglobalinvestmentbankstopartnerinpaneuropeantradingventure.htm`.

[19] See the next subsection for further details about MilleniumIT.

III. Competition between the LSE and MTFs

MTF Development. The increasing market fragmentation is not only a consequence of regulatory changes induced by MiFID. Especially technological progress and the emergence of HFT considerably lead to the rise of MTFs. These alternative trading venues seem to provide better solutions to speed sensitive market participants compared to traditional exchanges. MTFs invested from scratch into newest and fasted trading technology to offer a surrounding which attracts HFT order flow, e.g. a high throughput rate combined with innovative customized fee models and order types. A high throughput rate, i.e., the average message number that is processed by a system in a given time, is particularly important for algorithmic trading strategies which are based on fast order submissions and cancellations.

Besides the early technological orientation of MTFs, they also benefit from cost advantages compared to regulated markets. These cost advantages mainly results from regulatory differences to traditional exchanges. MTFs have, for instance, lower market surveillance requirements compared to traditional exchanges. Also the absence of a listing department – with all strings attached to it – reduces MTFs' expenses.

Another important influence to the increasing growth of MTFs is associated to their ownership structure from which MTFs may receive a significant share of routed orders. Apparently, major investment banks see a lot of potential in creating competition with traditional exchanges. During 2009, Chi-X, the largest European MTF, was owned by a consortium of large investment banks, including BNP Paribas, Citadel, Citigroup, Credit Suisse, Fortis, GETCO Europe Ltd, Goldman Sachs, Merrill Lynch, Morgan Stanley, Nomura Holding, Optiver, Societe Generale, and UBS. Obviously, instead of supporting their competitors, these institutes benefit from routing their orders to a trading venue where they hold shares of. Some of the same players also set up Turquoise in 2007 to compete head-to-head with domestic stock exchanges in Europe, in particular the LSE (e.g., Citi Group, Credit Suisse, Deutsche Bank, Goldman Sachs, Merrill Lynch, Morgan Stanley, and UBS). BATS Europe is owned by BATS Global Markets, an investment firm based in Kansas City, Missouri, USA. Also the ownership structure of the

Date	Description
October 1986	*Big Bang*, deregulatory changes & introducation of SEAQ at the LSE
October 1997	Introduction of SETS at the LSE
March 2007	Chi-X begins trading in 5 Dutch stocks and 5 German stocks
April 2007	Chi-X extents trading to all DAX 30 and AEX 25 constituents
June 2007	Chi-X begins trading in 11 FTSE 100 stocks & introduction of TradElect at the LSE
June 2007	Chi-X begins trading in all FTSE 100 stocks
October 2007	Chi-X extends trading to all CAC 40 stocks
October 2007	LSE acquires Borsa Italiana
August 2008	Pan-European trading platform Turquoise launched
October 2008	Launch of BATS Europe which trading LSE, Euronext and Deutsche Boerse stocks
September 2009	LSE acquires MilleniumIT
December 2009	LSE's darkpool Baikal merges with Turquoise
February 2011	BATS Global Markets acquires Chi-X Europe

TABLE 2.2: ***Important events at the LSE, Chi-X, BATS, and Turquoise.***

American mother-company reveals numerous large investment banks such Citi Group, Credit Suisse, Deutsche Bank, JP Morgan, Morgan Stanley, and, Merrill Lynch.

Table 2.2 outlines the most important steps of the UK trading landscape with regard to the LSE, Chi-X, BATS, and Turquoise. After having discussed the major developments of the LSE in the previous section, I now address its three major MTF competitors.

Chi-X was the first MTF that traded European equities. It started in March 2007 with a small set of German and Dutch stocks, but soon offered trading in the full set of DAX 30 and AEX 25 constituents right after the trial period. In August 2007, Chi-X also traded all FTSE 100 constituents and soon after that all CAC 40 stocks. BATS Europe operated the BATS trading platform during this time and offered trading in all FTSE 100 constituents in October 2007, while Turquoise started trading these and other European stocks already in August 2007.

Trading model and trading speed. The competition for order flow between traditional exchanges and MTFs is mainly based on trading costs and execution speed. In general, the LSE and the three MTFs exhibit the same trading model. They are organized as fully electronic limit order books. During my observation period, continuous trading opens at 8:00 and closes at 16:30 GMT on all platforms.

On the LSE, FTSE 100 constituents are traded on the Stock Exchange Trading System (SETS) but as mentioned in the previous section dealers may still provide liquidity off book. Unlike MTFs, trading at the LSE starts with a 10-minute opening auction and ends with a 10-minute closing auction prior and post continuous trading hours. Besides regular market and limit orders which represent visible liquidity, all trading venues offer further order types that are related to hidden liquidity. For example, market participants may submit iceberg orders or fully hidden limit orders. Iceberg orders are a type of limit order that display only a small peak of their actual volume. Thus, market participants do not have to reveal directly, whether they want to buy or sell a large position. The same accounts for fully hidden limit orders. They are not visible at all to any market participant. However, fully hidden limit orders have to meet the large-in-scale considerations of MiFID in order to be waived from pre-trade transparency as mentioned in Section 2.1.[20] On all four trading platforms, orders are executed according to a strict price-visibility-time priority. Thus, visible orders which are submitted to the order book with the same price as an iceberg or hidden order will be executed with priority. The LSE was the last trading venue that introduced fully hidden liquidity towards the end of 2009 (London Stock Exchange, 2009a).[21]

While MTFs have created their trading model to suit speed-sensitive investors, traditional exchanges had to adjust for this new traders clientele (see LSE's investments in Table 2.2). HFT has flourished over the past years and with them the need for faster trading technologies.[22] Several scholars argue that low latency leads to increased liquidity and thus to better chances for order placement at the right time (Riordan and

[20]In order to determine whether an order is large in scale compared to a normal order, the ESMA reviews orders on a yearly basis and sets the standard for normal orders, see also `http://mifiddatabase.esma.europa.eu`.

[21]The LSE introduced hidden liquidity not before the end of 2009. Therefore, I exclude all inside-the-spread (hidden liquidity) executions of the LSE prior to December 2009 from my empirical analysis. Apparently, these executions are data errors.

[22]To date, the trading volume of algorithmic and high frequency traders in most European blue chip indices reaches between 40% to 60%, see `http://hft.thomsonreuters.com/`.

Storkenmaier (2011)).[23] Unlike to their human counterparts, algorithmic and high frequency traders place, cancel, or execute a multitude of orders within milliseconds.

Even if MTFs concentrated from the very beginning on fast trading technology, this does not exclude them from continuously updating their trading systems. Thus, during 2009 all four trading venues were heavily investing in new technology with regard to their trading infrastructure. While all MTFs offered round-trip latencies at the end of 2008 in a range under 2 milliseconds, the technological race towards the sub-millisecond area was pushed forward quickly during 2009.

Turquoise was the first platform to announce a series of upgrades to improve response times and capacity on its platform. They claimed that upgrades will improve its maximum achievable throughput by 150% and reduce end-to-end response time latency to below one millisecond.[24] At the second anniversary of Chi-X on March 30, 2009, Chi-X stated that their co-location latency is of 400 microseconds and internal latency of 350 microseconds.[25] In June 2009, BATS Europe also claimed that *«[...] with an average round trip response of 380 microseconds, BATS Europe already delivers some of the fastest, sustained response times in the industry with world-class, sustained low latency[...]»*.[26]

With latencies of nearly 4.6 milliseconds at the end of 2008, the LSE had to react on these heavy technology investments of its competitors. For this reason, the LSE bought MilleniumIT in September 2009. MillenniumIT's high performance technology provides the LSE with a highly scalable and very low latency in-house developed trading system with quicker product speed to market.[27] In comparison to the 2009 latencies, LSE and Turquoise today offer latencies over their MilleniumIT co-location service platform with an average 99 percentile latency round trip time of 125 microseconds for the

[23] For a discussion of the need for higher trading speed, see `http://www.ftmandate.com/news/fullstory.php/aid/2335/The_need_for_speed.html`.

[24] See `http://www.thetradenews.com/news/Asset_Classes/Equities/Turquoise_upgrade_to_deliver_sub-millisecond_latency.aspx`

[25] See `http://www.businesswire.com/news/home/20090330005118/en/Chi-X-Europe-Celebrates-Anniversary`

[26] Quote of BATS Chief Operating Officer Paul O'Donnell, BATS press release from June 2009. `http://cdn.batstrading.com/resources/press_releases/FixnetixBATSHosting_FINAL.pdf`

[27] See, LSE press release 36/09 `http://www.londonstockexchange.com/about-the-exchange/media-relations/press-releases/2009/london-stock-exchange-group-to-acquire-millenniumit-for-us30m-18m.htm`

London Stock Exchange Market and 100 microseconds for the Turquoise Cash Equity market.[28]

Innovative fee models. Due to the increased frequency of order submission, cancellation and execution, transaction costs may increase particularly for HFT. Therefore, innovative fee models may attract these kind of traders which bring a large portion of today's trading volume. MTFs were among the first trading venues which focused on HFT needs in their fee models. Hence, the price differences in trading fees between the LSE and MTFs may also add to the shift away from the regulated market. During my observation period the fee structure of all trading venues is subject to frequent changes, except for Turquoise. Table 2.3 gives and overview of the fee schedules during 2009 on the different platforms.

However, the innovation does not merely come with reduced fees compared to the traditional exchange, but also with a new tariff system called "maker-taker". At the beginning of 2009, all platforms had installed a maker-taker tariff system.[29] Maker-taker tariff systems charge investors for aggressive (taker/market orders) orders that consume liquidity from the order book, i.e., these orders are executed against outstanding limit orders in the order book. For executed passive (maker/limit) orders that provide liquidity to the order book, investors receive a rebate.

At the beginning of 2009, the LSE charged an investor between 0.45 bps and 0.75 bps of the order volume for aggressive orders. Passive orders received a rebate of up to 0.40 bps. On September 1, 2009, the LSE lowered transaction fees and switched back to a traditional fee scheme charging both aggressive and passive orders between 0.20 bps and 0.45 bps depending on the monthly trading volume of an investor.[30] Chi-X and

[28] See LSE website, `http://www.londonstockexchange.com/products-and-services/connectivity/hosting/hosting.htm`.

[29] The LSE quickly adopted the maker-taker tariff system to its fee model due to the competitive pressure. Yet, it decided to switch back to the old-fashioned tariff system on September 1, 2009. See `http://www.thetradenews.com/magazine/The_TRADE_Magazine/2007/September/Both_sides_of_the_trade.aspx` for a discussion about the competitive pressure of maker-taker tariff systems.

[30] LSE chief Xavier Rolet said: *"Maker-taker pricing relies on the concept that posting a passive order is a superior, more valued kind of liquidity. We believe that passive and aggressive orders are equally valuable. We do not want to favor one type of client over another."*, see `http://www.finextra.com/news/fullstory.aspx?`

Trading Venue	Market Order	Rebate	Date	Add. Info
LSE	0.45 - 0.75	up to 0.40	Until 08/2009	Rebate depending on volume
LSE	0.20 - 0.45	no more rebates	From 09/2009	Fee depending on volume
Chi-X	0.30	0.20	Entire 2009	Regular fee schedule
Chi-X	0.30	0.30	10/2009	Trade promotion, rebate depending on volume
BATS	0.30	0.20	From 01-08/2009	Regular fee schedule
BATS	0.20	0.40	09/2009	Trade promotion, rebate depending on volume
BATS	0.25	0.30	Starting 10/2009	Aggressive order fee reduction
Turquoise	0.28	0.20 - 0.24	Entire 2009	Rebate depending on volume

TABLE 2.3: ***Fee models of the LSE, Chi-X, BATS, and Turquoise in 2009.*** *All numbers are refered to as basis points. The rebates are given for passive, liquidity providing orders and have to be subtracted from market order fees.*

BATS charged investors 0.30 bps for an aggressive and rebate an executed passive order with 0.20 bps during 2009. However, both platforms offered special inverted pricing promotions for investors during the year. Chi-X offered customers under certain volume conditions a free trade environment by offering a rebate of 0.30 bps on aggressive orders in October 2009. BATS even subsidized trades by offering customers a 0.40 bps rebate for executed passive orders while charging aggressive orders with only 0.20 bps during September 2009. From October 2009, BATS lowered its constant tariff schedule to 0.25 bps for aggressive orders while keeping the rebate for passive. On Turquoise, investors pay 0.28 bps for an aggressive order and receive a rebate between 0.20 bps and 0.24 bps for executed passive orders depending on the traded volume.[31]

newsitemid=21315.

[31]See, http://www.londonstockexchange.com/about-the-exchange/media-relations/press-releases/2009/london-stock-exchange-introduces-new-orderbook-trading.htm, http://www.thetradenews.com/asset-classes/equities/3673, http://www.chi-xeurope.com/trading-notices-pdfs/trading-notice-0183.pdf, http://www.tradeturquoise.com/market_notices/tariff_Schedule.pdf.

Increased HFT activity on MTFs (Menkveld, 2011b) may particularly be due to these reduced fee structures and innovative fee models that MTFs offer. HFT often uses passive, liquidity providing orders to manage their inventory control (Kirilenko et al., 2011). Low maker-taker fees consequently add to further increasing HFT trading profits.

Influence on market shares. The competitive factors outlined above, have strongly influenced the distribution of trading volume in such a fragmented trading landscape. Figure 2.1 displays the monthly share of electronic order book trading turnover of the LSE, Chi-X, BATS, and Turquoise from 2008 to 2012. The figure marks a continuous loss in turnover of the LSE, formerly Europe's largest trading venue also compared to other national exchanges.[32] Unfortunately, the Federation of European Securities Exchanges (FESE) does not provide statistics for BATS and Turquoise before October 2008 and January 2009, respectively. According to FESE, Chi-X captured the position as Europe's largest trading venue for the first time in August 2011. Almost in parallel, BATS Global Markets, the owner of BATS Europe decided to acquire Chi-X Europe and the merger was completed at the end of November 2011.[33] Therefore, data in figure 2.1 on BATS expires after 2011 and the turnover volume of the joint entity BATS Chi-X Europe is listed as Chi-X after January 2012.

[32]See `http://www.fese.be/en/`.
[33]See BATS Chi-X Europe (2011).

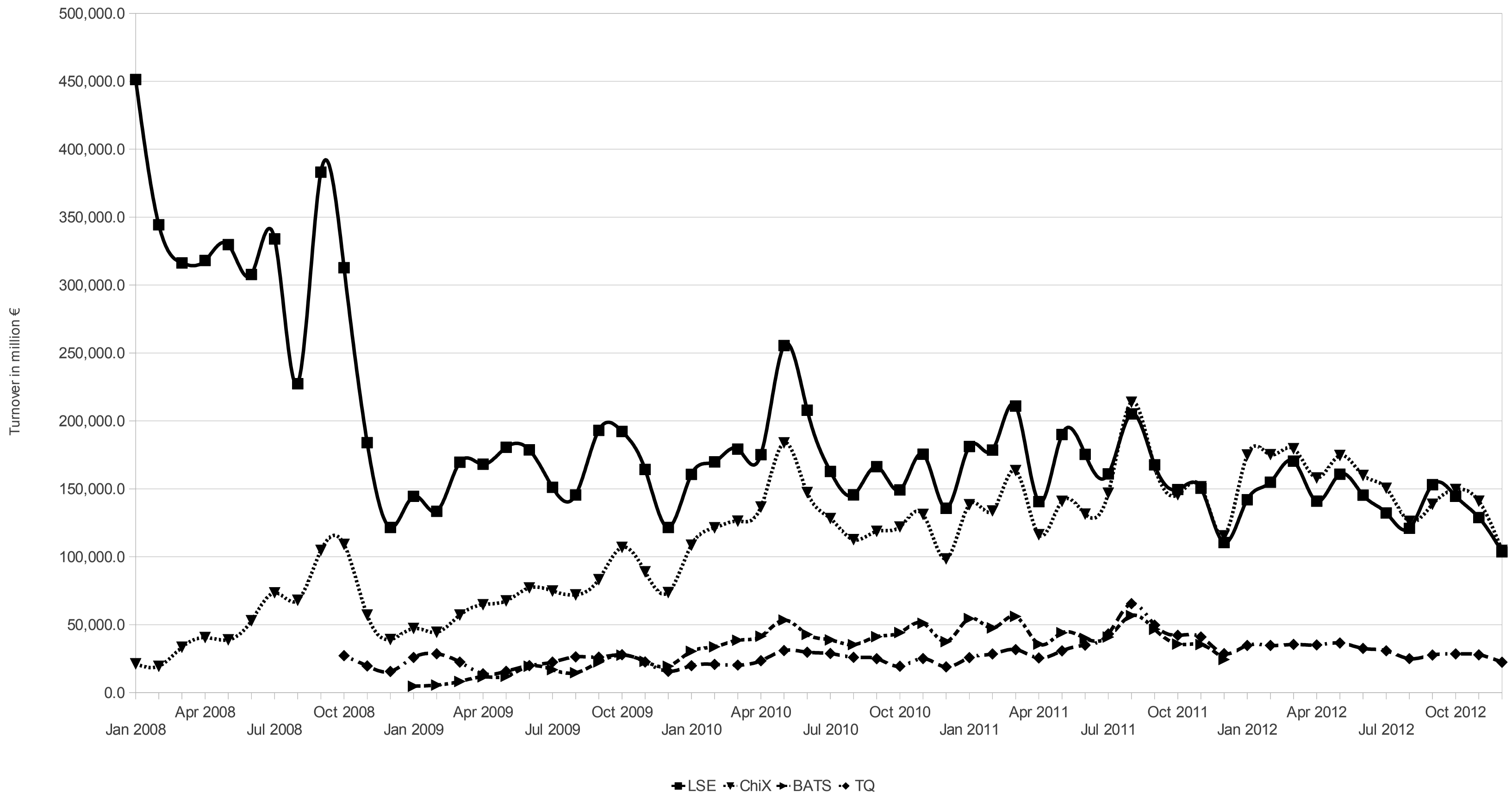


FIGURE 2.1: ***UK monthly order book turnover of LSE, Chi-X, BATS, and Turquoise.*** *The figure shows the electronic order book equity trading turnover in EU listed equities at each trading venue from 2008-2012. BATS Europe took over Chi-X in 2011. From January 2012 Chi-X and BATS trading volume is merged and the new trading platform is called BATS Chi-X Europe. According to FESE market statistics, BATS Chi-X is the largest trading platform in Europe in terms of trading volume; Source: Federation of European Securities Exchanges.*

In order to get a detailed picture of my 2009 observation period, I calculate weekly market shares of the four trading venues from the consolidated order book data that I use throughout my thesis.[34] During my observation period, the LSE, Chi-X, BATS, and Turquoise account for roughly 99% of non-OTC trading volume in FTSE 100 constituents.[35] Figure 2.2 depicts the development of weekly market shares in FTSE 100 constituents traded on the LSE, Chi-X, BATS, and Turquoise between January 2 and December 30, 2009. This figure is based on my data sample that consists of 69 FTSE 100 stocks.[36]

It shows a clear shift in market shares away from the LSE towards the three MTFs. While LSE's market share dropped from 74.8% in January 2009 to 57.6% at the end of 2009, Chi-X and BATS increased their share in trading volume. Chi-X, the largest European MTF during 2009, almost doubled its market share in FTSE 100 constituents from 14.7% to 27.3% over 2009. BATS's market share more than quadrupled from 2.1% to 9.3%. Turquoise is the only trading venue which lost market shares during my observation period. Its share in trading volume decreased from 8.5% to 5.7% over the year.

[34]See Chapter 4 for further explanations.

[35]See `http://fragmentation.fidessa.com` for further details.

[36]See 4.1 for details of my sample selection.

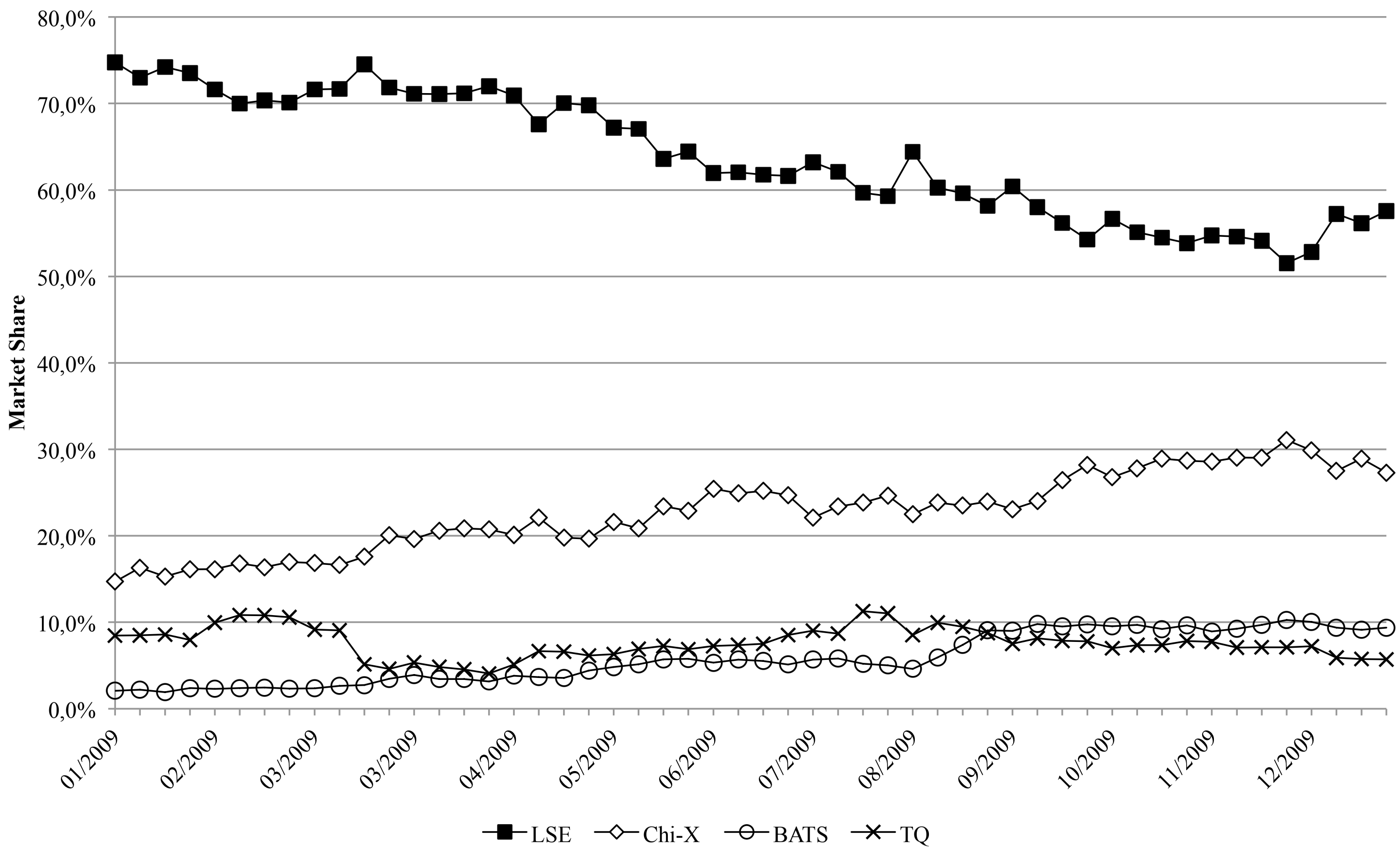


FIGURE 2.2: ***Weekly FTSE 100 trading volume on the LSE, Chi-X, BATS, and Turquoise.*** *The figure shows average weekly trading volume of the FTSE100 constituents on the LSE, Chi-X, BATS, and Turquoise from January 2009 to December 2009. First, daily market shares are obtained by multiplying the daily closing price of an instrument on each trading venue with the corresponding number of shares traded. Second, daily trading volume is averaged across instruments on a weekly basis.*

Chapter 3

Related Work

"The last two decades have seen a tremendous growth in the academic literature now known as market microstructure, the area of finance that is concerned with the process by which investors' latent demands are ultimately translated into transactions. Interest in microstructure and trading is not new but the recent literature is distinguished by theoretical rigor and extensive empirical validation using new databases."

Madhavan (2000)

Chapter Overview. This chapter contains theoretical and empirical work which is closely related to my research questions. I focus mainly on three categories of research papers which are all connected to market microstructure literature. The first category is addressed in Section 3.1 and deals with theoretical and empirical studies related to intermarket competition. The second category, Section 3.2, covers intraday trading patterns on different trading venues. The third and last category, Section 3.3, focuses on the influence of technological changes as well as new market participants and their influence on the trading landscape.

3.1 Intermarket Competition

THE relationship between fragmentation and market quality is ambiguous from a theoretical as well as from an empirical perspective. Intuitively, fragmentation should have a detrimental effect on market quality through scattering order flow and liquidity across various trading venues as this decreases the probability of matching buy and sell orders. Yet, there are different aspects to be considered, as for instance the effects of increased competition, which might mitigate negative effects stemming from fragmentation. The following section gives an overview of both, theoretical and empirical literature which address the manifold relationship between market fragmentation, competition, and market quality.

I. Theoretical Literature

Particularly theoretical literature in market microstructure point to the problems which are connected to a fragmented market environment. Mendelson (1987) theoretically addresses the impact of fragmentation on market quality. He argues that compared to a single market, multiple trading venues induce higher search and communication costs for investors (Mendelson, 1987, p. 190). He models the influence of fragmentation on market quality by using competitive and consolidated trading venues. His results indicate that fragmented trading venues significantly reduce expected trading volume, increase price variance, and lower expected trading profits for investors.

Literature also refers to positive effects of network externalities on liquidity, which point to a centralization of trading. For example, Pagano (1989b) analyzes a two market scenario with equal trading costs at both markets. He argues that when new traders enter the market, they take into account the entry decision of others which will thus shift trading to one market. This trading bias will lead to an increase in liquidity on this particular market and thus trigger more trading to shift there. Additionally, he states that fragmentation is welfare reducing. Contrarily, concentrated trading is Pareto-improving given the assumption that search costs are zero.

Chowdhry and Nanda (1991) study a multi-market scenario with a few large-scale informed investors and many noise traders. They show that in equilibrium, noise traders tend to choose the most liquid market and route their order towards it in order to benefit from lower implicit trading costs. This will reversely attract more informed traders who place their orders where many uninformed traders act so that they can hide their superior information. As a consequence, liquidity increases on this trading venue.

Following the arguments of both, Pagano (1989b) and Chowdhry and Nanda (1991), trading should best be centralized. Yet, despite higher search costs and positive network externalities new trading venues keep appearing which calls for other theoretical models that address this fact. Madhavan (1995) shows in his model that fragmentation is related to trade disclosure. Under the assumption that markets are not closely connected and trade disclosure is not an obligation, market participants may actually benefit from fragmentation. In his scenario, traders enjoy the advantage of hiding large trades better than within a concentrated trading environment and market makers benefit from reduced price competition. Yet, he also states that «*[. . .] fragmentation increases price volatility and induces other distortions as well[. . .]*»(Madhavan, 1995, p. 581).

In summary, theoretical results are mixed and point to both, reasons why trading should concentrate to increased market quality (e.g., search costs and network externalities) but also reasons why order flow may spread across trading venues (e.g., hiding large positions and superior information).

II. Empirical Literature

From an empirical perspective, market fragmentation and competition are closely connected and may have as well ambiguous effects on market quality. New trading venues may force old trading venues to innovate in various ways. Increasing price pressure to gain market share is just one factor. Yet, new trading venues often enter the market with superior technology or better services compared to their long established competitors. This increases the need to innovate for traditional trading venues in order not to lose further market shares.

Academic Article	Markets	Fragmentation
US Studies		
Demsetz (1968)	NYSE & Third Market	+
Tinic (1972)	NYSE & Third Market	+
Hamilton (1979)	NYSE & Third Market	~/+
Hasbrouck (1995)	NYSE & Third Market	~
Easley et al. (1997)	NYSE & CSE	-
Battalio et al. (1997)	NYSE & Third Market	+
Boehmer & Boehmer (2003)	NYSE & Several	+
Bennett & Wei (2006)	NYSE & NASDAQ	-
O'Hara & Ye (2011)	NYSE & Third Market	+
EU Studies		
Foucault & Menkveld (2008)	AEX & LSE	~/+
Hengelbrock & Theissen (2009)	Third Markets & Turquoise	~/+
Degreyse et al. (2011)	Third Markets	~/+
Riordan et al. (2011)	LSE & Third Markets	+
Kohler & von Wyss (2012)	AEX & LSE	+

TABLE 3.1: ***Overview of related literature: Intermarket competition***

Market microstructure literature offers a rich selection of studies which address these ambiguous effects of fragmentation and competition on market quality. The following section summarizes several empirical findings and concentrates hereby on the US and Europe. Table 3.1 provides an overview of the studies which are presented below and indicates whether the studies find positive, negative, or ambiguous effects of market fragmentation on market quality.

US market studies. Early empirical studies that address competition between different markets, find mixed results with a positive bias, speaking in favor of fragmentation. Demsetz (1968), Tinic (1972), and Hamilton (1979) are among the first studies to deal with fragmentation. They all concentrate on competition between the NYSE and US regional exchanges. They use various stock samples, which are traded on the NYSE and various third markets to address the effects, benefits, and costs of competition in fragmented markets. A major result of these studies is that competition for order flow leads to increased liquidity, which can be measured by decreasing quoted spreads. Yet, Hamilton (1979) also mentions negative effects which may stem from fragmentation. He finds that fragmented trading reduces trading efficiency at the reference market

(NYSE) which is negative for the overall market. However the competition effect which leads to a general larger market liquidity overrules the efficiency loss at NYSE.

In a more recent study, Bennett and Wei (2006) highlight further negative effects of market fragmentation on quoted spreads and liquidity. Bennett and Wei (2006) concentrate on the effect that is associated from a listing switch from NASDAQ to NYSE. The authors argue that NASDAQ traded stocks face a higher degree of order flow fragmentation since they are traded by a large number of other trading venues. They find that after switching the listing to NYSE, a stock's order flow becomes more consolidated and therefore experiences higher market quality measures as well as increased price efficiency. In particular, the authors choose 39 US companies that voluntarily switch their listings from NASDAQ to NYSE from 2002 to 2003. After switching to NYSE, the authors find particular improvement in various liquidity measures and also a reduction of short-term volatility. Their sample shows that particularly small cap stocks benefit from a switch from NASDAQ to NYSE over proportionally.

Other scholars not only concentrate on the effects of implicit trading costs and liquidity in fragmented markets. Hasbrouck (1995) addresses another interesting detail with regard to intermarket competition. In a set of securities which are tradeable on multiple markets, he develops an econometric approach to determine which market leads in the price discovery process. He aims to find which market incorporates new, price affecting information first. His sample covers the 30 stocks of the Dow Jones Industrial Average from August until October 1993. These stocks are traded on the NYSE but also on other US regional exchanges. He argues that a stock which is traded on several markets incorporates an implicit efficient price which is common to all markets. The sources of variation in this efficient price are connected to the different markets. Thus, his developed measure called – *"information share"* – is defined as «*...the proportion of the efficient price innovation variance that can be attributed to a particular market*». Put differently, he measures the influence of a market on the variance in the random walk process the stock price.[1] His findings point to a larger information contribution of the NYSE with

[1] I apply this method in my empirical research part in Chapter 6. I discuss the details of this measure in the methodology part in Section 4.2.3.

a median information share of 92.7% compared to the other markets (Hasbrouck, 1995, p. 1197). The findings of Hasbrouck (1995) underline the importance of the traditional reference market which is also pointed out by Easley et al. (1996).

Easley et al. (1996) focus on the information content in fragmented markets. They argue that competition may reduce the monopoly power of traditional exchanges and consequently result in overall better execution and prices for traders. Yet, the authors argue that liquidity is crucial for a market's price discovery. Scattering liquidity across various markets may restrict the ability of prices to aggregate information accordingly and thus reduce overall market efficiency. They state that such a scenario may even worsen if markets focus on competition of particular components of order flow. The authors analyze a stock sample traded at the NYSE and the Cincinnati Stock Exchange (CSE) during 1990. In these stocks, CSE dealers had retail order purchase agreements with a NYSE broker firm, i.e., CSE dealers bought uninformed retail order flow from NYSE brokers, which has been a common practice in the US since the late 1980ies (Easley et al., 1996, p.812). The authors claim that this practice is used to *'cream-skim'* uninformed liquidity from the NYSE. This increases adverse selection risk at the NYSE because their amount of information based trades increases relatively. To cope with increased potential risk of being adversely selected by informed traders, NYSE specialists will most likely widen their spreads. This, however, will trigger decreasing welfare effects for the market in general, since the NYSE represents the reference market for all other exchanges.

However, there are also several recent studies which address mainly positive effects of market fragmentation to overall market quality, or they contradict the results of older studies which show negative effects of market fragmentation:

Battalio et al. (1997) as well as Boehmer and Boehmer (2003) concentrate on the effects of fragmentation on market quality when a new competitor enters the market. Battalio et al. (1997) provide evidence that increased competition in NYSE listed stocks leads towards smaller quoted and effective spreads. They use an event study approach to analyze the effects of fragmentation on stocks that are additionally traded by a new market maker firm (Bernhard L. Madoff Investment Securities) on NYSE that competes with existing market maker firms. Boehmer and Boehmer (2003) study the impact of new NYSE trading activity in 30 ETFs which are listed and traded on the American Stock Exchange (AMEX) as well as several other trading venues. After just a month, NYSE captured more than 10.0% of overall trading volume, mainly drawn from AMEX. The authors find a strong decrease in quoted and effective spreads on all exchanges which trade the 30 ETFs. They also find no indication that increased competition affects price discovery negatively in terms of adverse selection.

In a more recent study, O'Hara and Ye (2011) contradict the results of Bennett and Wei (2006) who find that stocks benefit from a less fragmented trading environment if they are listed at the NYSE. O'Hara and Ye (2011) argue that the results of Bennett and Wei (2006) mainly stem from sample selection biases, as their sample consists mainly of large cap stocks. Instead, the effects shown by Bennett and Wei (2006) may rather be explained by different trading rules or corporate governance requirements between the two exchanges (O'Hara and Ye, 2011, p. 469). Compared to the 39 voluntary switches from NASDAQ to NYSE, O'Hara and Ye (2011) analyze the effects of market fragmentation on 262 NASDAQ and NYSE listed stocks from January until June 2008. Their overall result is that fragmentation does not harm market quality. They argue that market fragmentation is pushing order flow competition particularly in less liquid stocks which thus benefit from increasing fragmentation. Despite arguments which are in favor of a trading consolidation, e.g. network externalities, the authors claim that positive effects of fragmentation on market quality prevail. As a main reason for this conclusion they state that the US market – even being spatially apart – is virtually connected via smart order routing technologies, a consolidated tape that aggregates quote and trade information from various platforms, and trade-through protection rules.[2]

[2] In a fragmented market environment, it may happen that dealers execute an order at a price worse than the best available quoted price in the consolidated market. Order executions which disregard price priority are so called *trade-throughs*. Ideally, dealers should avoid trade-through violations because they hinder market participant's liquidity provision via limit orders. Yet, for various agency based reasons, trade-through executions may economically be logical. Firstly, with regard to a dealer's monitoring costs and secondly, with regard to a dealer's additional time that he may require for splitting an order over several markets. In the US, Regulation NMS creates a consolidated tape of national best bid and ask and to the same time prohibits trade-throughs for all exchange-listed stocks. In Europe a trade-through prohibition does not exist. MiFID aims to control trade-through problems through extensive pre- and post trade transparency requirements, see 2.1.

In summary, empirical research papers which address US markets find mainly positive evidence of the influence of fragmentation on market quality. Particularly, implicit transaction costs and thus liquidity experience a positive effect with decreasing quoted and effective spreads (Battalio et al., 1997; Boehmer and Boehmer, 2003; O'Hara and Ye, 2011). Yet, fragmentation may also have a downside, as the risk of adverse selection may increase and thus reduce overall welfare (e.g., Easley et al., 1996).

European market studies. In Europe, the history of literature addressing market fragmentation is not as extensive as in the US. Yet, a growing number of research papers addresses the influence of MiFID induced competition on market quality and price discovery.

Foucault and Menkveld (2008) analyze market quality even before the introduction of MiFID. They concentrate on the Dutch stock market before and after the entry of a competing limit order trading system of the LSE, called EuroSETS, in 2004. Before LSE's market entry, Dutch stocks were mainly traded on Euronext.[3] Their sample includes 22 out of 25 stocks from the AEX index. Their main findings show a deeper consolidated order book after the LSE's market entry, as well as smaller trading cost for liquidity consuming market orders. The authors also demonstrate that competition between the two platforms quickly increases as Euronext reacts on the entry of EuroSETS with a fee reduction on limit orders. Additionally, Foucault and Menkveld (2008) address the problem of trade-troughs in a fragmented European trading landscape and argue that a trade-through protection for market participants seems important because trade-throughs reduce the profits of liquidity providers. They also point to other problems of market fragmentation as for instance the one-sided advantages of market participants who are able to use smart order routing systems.

Hengelbrock and Theissen (2009) analyze the market entry of Turquoise in 14 different countries in August and September 2008. Their results from a cross-sectional regression model point out that Turquoise captures particularly high market shares in stocks that can be associated with the following characteristics: Large market capitalization, relatively high free float in shares, previously high bid-ask spread in the home market

[3] Amsterdam Stock Exchange and Paris Bourse merged in 2001.

(representing less liquid stocks), and low volatility. With regard to an improvement of overall market quality after the entry of Turquoise, they find mixed results. Depending on the panel size of their regression model, they find that spreads in the home market may decline while spreads at Turquoise stay higher. In general, Turquoise managed to take away market share from the home market without offering higher liquidity which, according to the authors, represents a disciplinary effect on the home market.

Degryse et al. (2011) study the effect of MiFID induced fragmentation on order book depth for a sample of 52 large and mid cap Dutch stocks from 2006 to 2009. They argue that liquidity has different dimensions, i.e., global and local, and that not all market participants may have access to global liquidity. They define global liquidity by creating a consolidated order book based on individual order books of six trading venues that account for 99% of the visible order flow in these 52 stocks (i.e., Euronext, Deutsche Boerse, SIX, NASDAQ OMX, Chi-X, and BATS). They argue that market participants with SOR technology have access to this kind of liquidity. Yet, without SOR technology, market participants are left with only local liquidity from their home market (Euronext). They find that global liquidity increases across trading venues with the level of market fragmentation. However, local liquidity on the regulated home market, Euronext Amsterdam, decreases by nearly 10% relative to a completely consolidated market. They conclude that investors who only have access to Euronext Amsterdam may be worse off due to the change in market quality.

Riordan et al. (2011) compare market quality in FTSE 100 constituents on the LSE, Chi-X, BATS, and Turquoise during two periods of 29 days each in 2009 and 2010. Their results indicate that increasing fragmentation prompts an improvement of market quality on each trading venue. During their 2010 observation period, Chi-X and Turquoise are more liquid – measured by quoted and effective spreads – than the home market LSE. Similar to Degryse et al. (2011), the authors state that market participants may benefit from trading on multiple platforms. Additionally, they find a shift in price discovery away from the LSE towards MTFs over time. During their 2010 observation period, prices 'move first' on Chi-X. Overall, they provide evidence that MTFs contribute positively to market overall quality.

Kohler and von Wyss (2012) address similar research questions as Riordan et al. (2011) for a final sample of 29 stocks listed on the Swiss exchange, Chi-X, BATS, and Turquoise. Yet, they focus on a long-term sample, covering 20 months from November 2008 until June 2010. The results of their multivariate regression models reveal no sign of market quality deterioration in the aftermath of MiFID. In particular, they find that fragmentation is more pronounced for large cap stocks, i.e., MTFs exhibit a higher market share in trading large cap firms.

In summary, scholars who address the influence of regulatory changes on the European equity market find that market fragmentation increased significantly after the introduction of MiFID. Particularly MTFs captured a large share of order flow from traditional, regulated markets, especially in large cap stocks (Hengelbrock and Theissen, 2009; Kohler and von Wyss, 2012). Most studies attribute positive effects to market fragmentation as for instance an increase in overall liquidity or a shift in price discovery towards MTFs (Degryse et al., 2011; Riordan et al., 2011). However, the lack of a consolidated tape as in the US, which transparently displays best European bid and ask prices, makes the overall liquidity increase become one-sided to market participants that can actually afford trading in multiple markets via SOR (Degryse et al., 2011).

3.2 Intraday Patterns

This section provides an overview of the main theoretical and empirical literature addressing intraday trading patterns in different markets. In general, most of the research papers which address intraday patterns have their focus on a single market.[4] Compared to most other studies, I particularly concentrate on intraday trading patterns in a multi-market scenario. In Chapter 5, I empirically compare intraday trading patterns on four different markets that actively compete for order flow. My idea is to find out whether a single market dominates others during particular times of the trading day and also whether increased market fragmentation changes existing intraday patterns over time. To provide a better overview, I also include my intraday results in Figure 3.1, which summarizes intraday results of other scholars.

I. Theoretical Literature

Theory points out that trading activity may not only concentrate geographically on individual trading venues but also during particular times within a trading day. The models of Admati and Pfleiderer (1988) and Brock and Kleidon (1992) provide theoretical explanations for the existence of intraday trading patterns on individual trading platforms.

Admati and Pfleiderer (1988) focus on reciprocal strategic decisions of informed traders, discretionary liquidity (noise) traders, and non-discretionary liquidity (noise) traders. A major invention of their model is to distinguish between liquidity traders that place their orders time-discretionary and other liquidity traders who just randomly place their orders. They argue that intraday patterns in volume and price volatility arise due to liquidity traders who deliberately choose to trade at discrete points during the trading day. According to the authors, a liquidity trader with discretion of his order placement will prefer to trade when *"the market is thick"*, i.e., a lot of volume is in the book so that his trading activity has less effects on prices (Admati and Pfleiderer, 1988,

[4]Werner and Kleidon (1996) are among the few authors that also compare intraday trading patterns of cross listed securities in the UK and the US.

p. 5). Their model shows that these periods also attract informed traders who try to conceal their superior information in periods of high trading activity. This leads to an increase of traded volume and price volatility at certain periods. According to the authors, opening and the closing of the market may represent such distinctive clustering points, due to intensive information arrival as well as portfolio rebalancing reasons. Yet, the clustering of distinct liquidity traders may also appear during other periods of the trading day, depending on the thickness of the order book.

Brock and Kleidon (1992) have a different focus in their model. They extend Merton (1971) who studies portfolio positions in a continuous market. They argue that market participants exhibit an increased and less elastic desire to trade at market opening and closing compared to other periods within the trading day. At market opening, portfolios have to be adjusted due to the arrival of new overnight information. Shortly before market closing, investors need to optimize their positions for the overnight period which again triggers increased trading activity. This trading behavior creates U-shaped patterns in traded volume. The authors also argue that spreads and volume are positively correlated. They justify larger spreads at open and close of the market because market makers may price discriminate market participants who need to rebalance their holdings during these periods.

II. Empirical Literature

Empirical literature on intraday patterns of trading intensity and market quality find varying results which do not necessarily follow theoretical predictions. Figure 3.1 summarizes empirical findings on intraday patterns of trading intensity, quoted spreads, and information based of trading at the NYSE, NASDAQ, and the LSE.

Trading intensity. Intraday trading intensity measures predominantly follow an U-shape on the NYSE and NASDAQ. Several authors argue that there is a strong correlation between trading volume and volatility (Jain and Joh, 1988; Foster and

Viswanathan, 1993). The authors point out that market uncertainty measured by increased return volatility is significantly higher at market opening and closing which thus leads to the U-shaped intraday patterns. McInish and Wood (1992) find a significant inverse relationship between quoted spreads and trading activity, i.e., trading activity increases while quoted spreads decrease during the trading day. Chan et al. (1995) concentrate on NASDAQ stocks. Despite structural differences between NYSE and NASDAQ, they also find trading to be most active at market opening and closing.

Results of intraday trading activity on the LSE is mixed. While Werner and Kleidon (1996) and Klussmann and Hautsch (2011) also find U-shape patterns, Abhyankar et al. (1997) and Cai et al. (2004) report a two-humped pattern for intraday volume and also no direct correlation between trading volume and volatility. Yet, the sample periods of Abhyankar et al. (1997) and Cai et al. (2004) are particularly small which may lead to biased results. The authors cover merely Q1 of 1991 and March to May of 2001, respectively.

Quoted spreads (liquidity). Empirical evidence on intraday quoted spreads is homogeneous across markets with increasing liquidity over the trading day. For example, McInish and Wood (1992) report a crude reversed J-shaped pattern of quoted spreads which is similar to empirical findings for the LSE. A slight exception holds for a sample of NASDAQ stocks. Chan et al. (1995) find decreasing quoted spreads only at the close of the market while liquidity changes little throughout the day. According to the authors, diverging patterns on NYSE and NASDAQ can be explained by structural market differences, i.e. NYSE is organized as a limit order market with specialists and NASDAQ as a market maker market. A possible reason for the decrease in quoted spreads on NASDAQ may be market maker inventory controls prior to market closing.

In a more recent study which is closely connected to my sample period, Klussmann and Hautsch (2011) study high-frequency movements in returns, volatility, and liquidity at the LSE from January 2007 until June 2008. The authors concentrate on the influence of intraday news arrival on the aforementioned factors. Their sample covers 39 stocks of the FTSE 100 which according to the authors represent roughly 70% of the FTSE 100

Market	Authors	Trading Intensity	Quoted Spreads	Informed Trading
NYSE	Jain and Joh (1988)	U-shaped	n/a	n/a
	McInish and Wood (1992)	Crude J-shaped	Crude reversed J-shaped	Declining over the day
	Foster and Viswanathan (1993)	U-shaped	n/a	Crude reversed J-shaped
NASDAQ	Chan et al. (1995)	U-shaped	Stable through day, but decreasing at market closing	n/a
LSE/MTFs	Werner and Kleidon (1996)	U-shaped	Crude reversed J-shaped	n/a
	Abhyankar et al (1997)	2-humped	Reversed J-shaped	n/a
	Cai et al. (2004)	2-humped	Reversed J-shaped	n/a
	Klußmann and Hautsch (2011)	U-shaped	Reversed J-shaped	n/a
	Spankowski et al. (2011)	LSE: U-shaped MTFs: Increasing over the day	LSE & MTFs: Reversed J-shaped	LSE and MTFs: Declining over the day

FIGURE 3.1: *Overview of related literature: Intraday patterns*

market capitalization (Klussmann and Hautsch, 2011, p. 324). Similar to other studies, they find decreasing spreads during the trading day and higher price uncertainty at market opening and closing. They point out that intraday news arrival has a significant influence on volatility and trading activity, but little influence on bid-ask spreads (Klussmann and Hautsch, 2011, p. 336). They state that intraday news release decreases continuously during the day and exhibits highest levels at market opening. This finding may thus be connected to increased market uncertainty at the beginning of the trading day.

Information content of trades. McInish and Wood (1992) and Foster and Viswanathan (1993) find characteristic patterns for informed trading over the trading day. The information content of trades peaks at market opening and decreases until market close. This finding may be connected to Klussmann and Hautsch (2011) who do not explicitly address adverse selection or information content in trades. However, they find continuously decreasing intraday news arrival which thus may lead to a reduction in the information content of trades. McInish and Wood (1992) also address the relationship between quoted spreads and information based trading. They define unusual large trade sizes as information based trading and find a direct connection to wider spreads. Foster and Viswanathan (1993) argue that adverse selection costs are high at market opening, fall during the trading day and increase before market closing. They also provide evidence for a direct relationship between high adverse selection costs and trading volume.

3.3 Technology and Innovation in Equity Trading

The equity trading landscape has changed rapidly over the past decade. Not only that most trading venues have replaced traditional floor trading with electronic limit order books, but also external innovations such as new information and communication technology have contributed to this change. Today, trading venues may be spatially apart. However, high speed internet connections and sophisticated order routing technologies, combined with new market participants who exploit latency below milliseconds, virtually connect trading venues worldwide. While traditional exchanges had to adapt to the digitalization of equity trading, MTFs were constructed from scratch to cope with this new era of high-speed electronic trading. MTFs concentrated on the requirements of a new trading clientele which emerged along with technological innovation and regulatory changes. Algorithmic and high frequency trading account for a large share of daily trading volume at most of the major trading venues.[5] This literature section presents academic papers that have addressed these changes and their influence on overall market quality and market fragmentation.

I. Theoretical Literature

Theoretical literature on competition between alternative trading venues or the influence of new high-speed market participants is quite scarce. Yet, Foucault et al. (2012) address the effect of news arrival on trades and prices with special focus on HFT. They develop a model that takes into account two different dimensions of an informed trading model: (1) accuracy and (2) speed. Their model includes an informed investor who continuously receives news about the payoff of a risky security. This investor has both, a greater information processing capacity and a higher speed of reaction to news than regular market makers (Foucault et al., 2012, p.2). One of their main findings states that adverse selection risk increases when informed investors have a speed advantage

[5] According to Bank of England, «*HFT firms are believed to account for more than 70% of all trading volume in US equities, 40% of volumes in US futures and 20% of volumes in US options. In Europe, HFTs account for around 30-40% of volumes in equities and futures.*»(Bank of England, 2010, p.17). See also `http://hft.thomsonreuters.com/` for details on HFT activity in European blue chip indices which is between 40% and 60%.

because they can buy just in advance of positive news and sell in advance of negative news. As a deduction of these findings, one could argue that uninformed traders will face a higher risk of being adversely selected on MTFs as they are particularly attractive for speed sensitive investors (Menkveld and Jovanovic, 2010, p. 2).

II. Empirical Literature

Also empirical work addresses MTFs' contribution to price discovery or information based trading. Hoffmann (2010) analyzes the impact of multi-dimensional best execution on liquidity supply for a sample of 67 French and German high volume stocks traded on Chi-X, Euronext and Xetra. He argues that informed trading is more pronounced on alternative trading venues and he finds a significant higher share of private information on Chi-X compared to the two traditional trading venues. Also Riordan et al. (2011) and Jung and Katzschner (2012) find in their UK and German data sets, respectively, that MTFs lead in price discovery, which indicates more informed trading on those venues. Additionally, these authors find increasing market quality with regards to overall liquidity levels.

Other scholars address further positive effects to HFT and algorithmic traders with regard to overall market quality. Menkveld (2011b) argues that these new market participants act through their trading strategies as new multi-venue market makers. He analyzes the introduction of Chi-X on the Dutch equity market, where the MTF competes for market share against the traditional trading venue NYSE Euronext. He finds that HFT is active in both markets. Yet, on Chi-X, HFT accounts for the largest share in trading. According to his paper, MTFs are particularly attractive to HFT for various reasons. On the one hand, HFT can act as multi-venue market makers due to speed sensitive environments which MTFs provide. On the other hand, MTFs offer lower fee structures. He argues that the emergence of HFT and MTFs create price pressure on traditional trading venues and the increased competition triggers positive welfare effects as for instance a reduction in bid-ask spreads.

Also Kirilenko et al. (2011) who study the effects of the May 2010 flash crash on NAS-

DAQ, find that HFT account for a significant share of market making activity due to their trading strategies. They often use passive, liquidity providing orders to manage their target inventory levels (Kirilenko et al., 2011, p. 23). Interestingly, the authors conclude that HFT did not trigger the flash crash, but contributed to exacerbated market volatility. Also Hendershott and Riordan (2009) support the finding that HFT fulfills market making tasks. They investigate high-volume stocks that are traded on Xetra during a short three week sample period in January 2008. Similar to Kirilenko et al. (2011), they address positive effects to HFT. In general, HFT seems to submit smaller orders than other market participants and continuously monitors the market. HFT consumes liquidity when it is cheap and supplies liquidity when it is expensive, which thus might be interpreted as market making activity that levels out liquidity differences over time.

Pagnotta and Philippon (2012) focus on competition in speed between the different trading platforms. They argue that – everything else being constant – all investors benefit from faster trading through MTFs and HFT (Pagnotta and Philippon, 2012, p. 4). This argument may explain why traditional exchanges lose market share if trading is faster and fee structures are more attractive on MTFs, particularly with the emergence of new speed sensitive traders. Yet, they also state that different investors have different preferences on trading speed. Accordingly, these investors must value other attributes of a trading venue as well. Competing trading platforms may acknowledge this fact by addressing the particular needs of different investor clientele.

Overall, there is more positive evidence which can be addressed to alternative trading venues and HFT in a fragmented market environment. In normal market conditions, MTF and HFT seem to actively contribute to market quality in a positive way. Yet, markets are not always in "normal" conditions. In fact, market turmoils with increased market and price uncertainty are as common as any other market period. It is a main objective of this thesis to look at the relationship between traditional exchanges and MTFs (combined with HFT activity) when trading does not exhibit a normal scenario.[6]

[6] My data sample does not allow my to identify HFT directly. Yet, from regarding existing literature, I suppose that HFT is much more active on MTFs than on traditional exchanges. I partially base my economical reasoning in Chapter 6 on this fact.

Only few authors have addressed the competitive relationship between traditional exchanges and MTFs when market conditions deviate from a normal setup. Gomber et al. (2012) are inspired by a crash scenario as for instance the May 2010 flash crash. They argue that European regulated markets use circuit breakers which may ensure price continuity and prevent potential crash scenarios.[7] While circuit breaker systems have already been implemented at European traditional exchanges, European MTFs have yet no circuit breakers in place. The authors argue that this may induce a scenario «*[. . .] where a single venue interrupts trading due to order imbalances but at the same time trading at alternative venues further proceeds, thus allowing volatility to cascade onto alternative markets*» (Gomber et al., 2012, p. 2). The authors are interested whether trading will shift towards MTFs when it is halted at the regulated market, which might thus pose a systemic risk to the overall European trading landscape. Their results indicate that volatility induced trading halts in a stock on the traditional exchange trigger a significant reduction of trading activity also on MTFs. This result reduces the fear of a systemic risk for the European trading landscape. However, it also points out that MTF price formation is to a large extent dependent on traditional exchanges which serve as reference markets.

This evidence hints to the free-riding behavior of MTFs on traditional exchanges price formation. In Chapter 6, I particularly address the competitive environment between traditional exchange and MTF in times of increased market uncertainty. I also identify further market conditions which influence the order routing behavior of market participants.

[7] A circuit breaker can be defined as a trading halt. Trading is stopped for (a) regulatory reasons, (b) technical reasons, or (c) market-based reasons. In general, all three reasons may happen, while market-based trading halts are amongst the most frequent ones. Usually, trading is stopped when prices disrupt due to abnormal order imbalances. Gomber et al. (2012) find in their Xetra data sample 464 trading halts in 27 stocks during 2009 (Gomber et al., 2012, p. 12).

Chapter 4

Data and Methodology

"Science is nothing but perception."

Plato (369, B.C.)

Chapter Overview. In order to perceive the desired correctly, an appropriate way of observing is crucial. This chapter provides important details about the data itself and my employed methodology. Section 4.1 addresses the selection and treatment of my data sample. Section 4.2 consists of four subsections and presents the measures that I created in order to analyze my presented research questions. In particular, I present measures for market fragmentation, various market quality and trading intensity measures, and a method for the identification of difficult market making days.

4.1 Selection of Data

IN order to analyze the influence of increasing market fragmentation on the relationship between a traditional exchange and MTFs, I concentrate on the largest and most fragmented market within Europe. During 2009, the UK equity market accounts for 29.1% of European equity trading volume. Additionally, FTSE 100 index constituents exhibit the largest degree of fragmentation within European blue chips (compare Section 2.2). Therefore, I regard this surrounding as most suitable for my empirical analyses.

To address my proposed research questions, I analyze the order books of the traditional exchange, the LSE, and the three largest European MTFs, which are Chi-X, BATS Europe, and Turquoise. During my observation period, these four trading venues account for nearly 99.5% of the non-OTC trading volume in FTSE 100 constituents (compare Section 2.2). The other 0.5% of non-OTC trading volume is traded mainly on Systematic Internalizers which are on the one hand not part of my proposed analysis framework. On the other hand, I have – unfortunately – no possibility to retrieve this kind of trade data to incorporate it into my analysis.

Observation periods. My data sample comprises order book information of the LSE, Chi-X, BATS, and Turquoise for all FTSE 100 constituents from January 5 until December 30 of 2009. The overall observation period includes 244 trading days in 2009. In the first empirical part of my thesis, I investigate

- the influence of increased market fragmentation on overall market quality and trading intensity at the four trading venues over time, and
- intraday competition between the trading venues.

To address intraday competition, I calculate and compare intraday trading patterns on all four trading venues for various measures. To capture the impact of increased market fragmentation on market quality and on intraday competition over time, I select two periods which exhibit distinct levels of market fragmentation. I select quarters Q1 from

January 2 until March 31, 2009 and Q4 from October 1 until December 31, 2009 as they exhibit quite distinct levels of fragmentation (see Figure 2.2). Also my fragmentation measure indicates a continuous increase over time, as stated in Figure 4.2. A comparison over time shows the different fragmentation levels. While average fragmentation in Q1 is 28.2% (median 28.6%) it increases to 45.7% (median 46.2%) in Q4 of 2009.[1]

My second empirical part of this thesis is based on daily aggregates to particularly exclude intradaily variations in my calculated measures.

Data Characteristics. For my analysis, I obtain trade and quote data for each trading venue from the Thomson Reuters DataScope Tick History archive through the Securities Industry Research Centre of Asia-Pacific (SIRCA).[2] I identify all FTSE 100 constituents with their Reuters Instrument Code (RIC) which serves as a unique identifier. For each stock, I fetch data for trade prices with the associated volumes, best bid and ask quotes with the associated volumes, and also bid and ask quotes up to three levels behind best prices. All trades and quotes are reported in British pence and are time stamped to the millisecond. The overall amount of trade and quote data for all four trading venues adds up to roughly 2.71 billion data points during 2009. In Appendix A, I display a snapshot sample of the raw trade and quote data for the LSE. The raw data structure of all MTFs looks similarly, except for the RIC and certain – platform specific – special qualifiers.

Filter criteria. To obtain a clean and homogeneous data set, I apply several filters to the individual order book trade and quote data, but also to supplementary firm level data. If a stock does not fulfill all necessary requirements with regard to data availability, it is excluded from the sample.

Trade and quote filters:

[1] Please see Section 4.2.1 for a detailed explanation of my fragmentation measure.

[2] The accuracy of the Thomson Reuters DataScope Tick History archive is also proven by the work and the comparison with international research databases by other scholars (e.g., Fong et al., 2011; Brockman et al., 2009). I thank the Karlsruhe Institute of Technology (KIT) and SIRCA (http://www.sirca.org.au/) for providing access to the Thomson Reuters DataScope Tick History archive.

- In my analysis, I focus on continuous trading from 8:00 until 16:30 GMT. In the raw data, all orders are time stamped to the millisecond and offer unique qualifiers to associate them to special market periods (e.g. opening, closing, or intraday auctions). Trades within these periods may bias my analysis and thus have to be excluded from the data sample. To retrieve the correct data, I use these unique qualifiers to delete reported executions within periods which are not of interest to my analysis.

- If a market order trades against several limit orders in one of the order books, this creates multiple data entries in the raw data. For each individual order book on each trading venue, I aggregate those kinds of individual orders to one single trade and combine all buy (sell) orders in a particular stock if they are reported within the same millisecond.

- In December 2009, the LSE was to last trading venue in my data sample to officially introduce hidden liquidity by the use of hidden limit orders (London Stock Exchange, 2009a). This type of limit order does not appear in the order book, however an incoming market order may be executed against it. Additionally, these orders have to meet certain large-in-scale considerations of MiFID to be waived from the pre-trade transparency. If a hidden limit order qualifies as such, it provides additional liquidity to the order book and offers the investor the possibility not to reveal his intention to buy or sell a large position – at least not until a market order is executed against it. Before the introduction of hidden liquidity a trade was always executed against best bid or ask (or multiple levels) in case of a (larger) sell or buy order. Now, an incoming market order may be executed against a hidden order and thus create an inside the spread execution. Since the LSE was the last trading venue to include these new order types at the very end of my observation period, I exclude all inside-the-spread executions at the LSE prior to December 2009 as these data entries are most likely data errors.

Firm level and filters:

- All selected stocks in my final data sample have to be included in the FTSE 100 index over the entire observation period, which means they have to be part of the index throughout 2009.

- I exclude companies with stock splits or other corporate actions. The corporate actions are obtained from Thomson Reuters.
- I further exclude stocks with missing trade and quote data or missing data on market capitalization.[3]
- Additionally, each selected stock has to be traded at least 10 times per day on each individual trading venue, i.e., the LSE, Chi-X, BATS, and Turquoise. This rule is necessary to guarantee a minimum quality of the measures which I calculate in the subsequent Section 4.2. At the beginning of 2009, particularly BATS and Turquoise show infrequent trading activity in some stocks which would bias overall estimation results and thus hinder an objective comparison.
- I also exclude nine trading days from my overall yearly sample due to infrequent trading. These days are either holidays or daily trading activity is considerably lower compared to the regular trading days. In the case that these days are no holidays, they may be connected to a non-banking holiday in UK or to a holiday abroad. For instance May 1st of 2009 is excluded, which is a typical holiday in many other European countries. Further, January 2 and December 31 of 2009 are excluded since they exhibit significantly smaller trading volumes which may bias my analysis.

My final firm sample leaves me with 69 stocks that fulfill the above filter criteria. I report my final firm sample in Appendix A where all included stocks are listed together with the LSE ticker symbol and the average daily market capitalization, as well as the average daily trading volume across all four trading venues during 2009. HSBC HOLDINGS is the most actively traded stock with an average daily trading volume of 64.4 mln GBP. The SAGE GROUP is least active in trading with an average daily trading volume of only 2.5 mln GBP. However, these volumes represent averages across all four trading venues. Trading volumes are significantly higher on the traditional exchange.

[3] I obtain daily market capitalization's per stock from Bloomberg.

For instance, HSBC HOLDINGS exhibits a daily trading volume of 182 mln GBP and the SAGE GROUP 6 mln GBP, respectively on the LSE.

Consolidated Order Book. For several measures in my analysis, I use both, the individual order books as well as the consolidated order book of all four trading venues. Particularly for my empirical analysis in Chapter 6, I use several aggregated measures which derive from the consolidated order book of the LSE, Chi-X, BATS, and Turquoise. I create the consolidated order book by integrating all four individual order books into a single order book on a per stock per millisecond base. Timestamps and RIC ticker symbols allow me to compute the consolidated best bid and best ask across all trading venues along with the associated volumes. Figure 4.1 demonstrates how I calculate the consolidated order book accordingly.

Order Book LSE	
Quote	**Volume**
545.50 (A)	400
545.45 (A)	200
545.35 (B)	400
545.30 (B)	200

Order Book Chi-X	
Quote	**Volume**
545.50 (A)	300
545.45 (A)	250
545.40 (B)	300
545.35 (B)	250

Con. Order Book	
Quote	**Volume**
545.50 (A)	750
545.45 (A)	550
545.40 (B)	300
545.35 (B)	800

Order Book BATS	
Quote	**Volume**
545.55 (A)	300
545.45 (A)	100
545.25 (B)	500
545.20 (B)	600

Order Book TQ	
Quote	**Volume**
545.55 (A)	100
545.50 (A)	50
545.35 (B)	150
545.30 (B)	200

FIGURE 4.1: ***Creation of a consolidated order book.*** *The figure exemplifies how I calculate the consolidated order book out of the individual order books of the LSE, Chi-X, BATS, and Turquoise from ask (A) and bid (B) quotes.*

4.2 Methodology

In my empirical analyses, I focus on the influence of increasing market fragmentation on trading intensity and market quality measures at the LSE, Chi-X, BATS, and Turquoise. In order to do so, I need to set up several measures which I can compare over time or during the trading day. In the following sections, I describe how I model (1) market fragmentation, (2) trading intensity and market quality measures, (3) a measure that concentrates on the information contribution of a single trading venue to overall price discovery in a fragmented market environment, and (4) a method to identify difficult market making days.

4.2.1 Market Fragmentation

Figures 2.1 and 2.2 illustrate how the UK equity market becomes more fragmented over time. I model fragmentation on a per stock per day level by the MTF trading share, also used in O'Hara and Ye (2011). It is defined as the volume share of stock i on trading day t traded on other markets (MTFs) than the traditional exchange (LSE):

$$Frag_{i,t} = 1 - \frac{Trad.Vol_{i,t}^{LSE}}{\sum\limits_{k \in K} Trad.Vol_{i,t}^{k}} \tag{4.1}$$

where $K = \{LSE, ChiX, BATS, TQ\}$ denotes trading venues accordingly. This measure is bounded in the interval $Frag \in [0,1]$, taking a minimum value of 0, if none of the volume is traded on MTFs. I use this particular measure for my empirical analysis in Chapter 5 to define two periods with distinct levels of fragmentation, Q1 and Q4 of 2009. In Chapter 6, I investigate several market factors that influence fragmentation over time in a panel regression model.

Figure 4.2 shows fragmentation and the detrended fragmentation measure over 2009. The measures are displayed as 10-days rolling means to avoid daily volatility and to better capture trends. From the figure it seems like the fragmentation measure is following an upwards trend and could thus be non-stationary (in mean). Therefore, I control the time series for stationarity using an Augmented Dickey Fuller (ADF) test (Dickey and Fuller, 1981). For modeling the ADF test, I include intercept and trend variables on the fragmentation time series, as both – intercept and trend – are clearly visible. The number of lags is chosen by the Akaike Information Criterion AIC (Akaike, 1974).[4] Results of the ADF Tests indicate that the null hypothesis $\beta_1 = 0$ (unit root) may be rejected for all tested time series which means that the time series are trend stationary.[5]

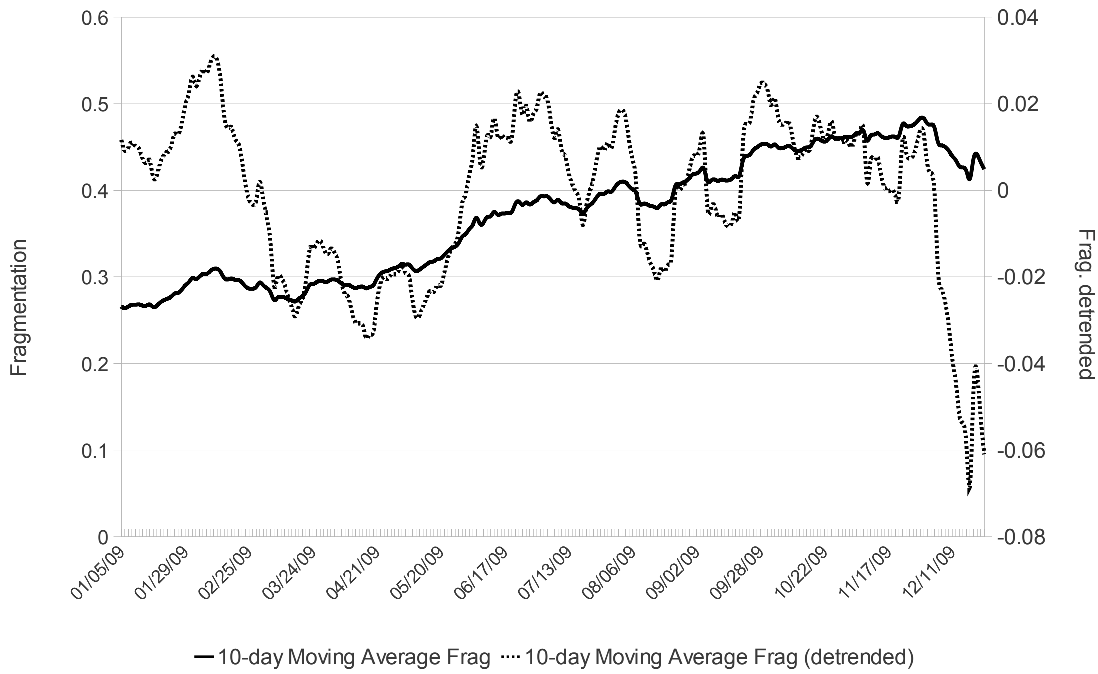


FIGURE 4.2: *10-days moving average of fragmentation and detrended fragmentation. The figure displays the 10-days moving average of the fragmentation measure calculated according to Equation 4.1 and the detrended 10-days moving average of this measure. I detrend fragmentation – assuming a deterministic trend – by taking the residuals from a linear regression model on time.*

Nevertheless, trends over time may influence regression results significantly. For this

[4]In Chapter 6, I also use market shares of the four trading venues for my regression models. As visible in Figure 2.2, Chi-X and BATS market shares also seem to follow a similar trend as my fragmentation measure while the LSE market share shows an inverted downward trend, respectively. I test all market share time series for stationarity accordingly.

[5]See Appendix A for unit root statistics of all tested time series.

reason, I detrend all time series (fragmentation, LSE/Chi-X/BATS/TQ market shares and information shares) – assuming a deterministic trend – by taking the residuals from a linear regression model of the relevant measures on time. Figure 4.2 displays the outcome of this regression model, here exemplified for the fragmentation measure (dotted line).

The availability of individual order book data of all four markets also enables me to calculate market shares of each trading venue relative to the three others. Since the four trading venues, LSE, Chi-X, BATS, and Turquoise account for nearly 99.5% of non-OTC trading volume in FTSE 100 constituents, I assume they represent the market as a whole. If the formerly predominant market LSE loses market shares to the others, fragmentation increases. The development of market shares delivers me thus not only an indication of overall market fragmentation, but also a detailed view on the influence of market fragmentation on each individual market. Market shares are calculated as follows:

$$Mkshare_K = \frac{Trad.Vol_K}{\sum_{k \in K} Trad.Vol_k}$$

where $K = \{LSE, ChiX, BATS, TQ\}$.

4.2.2 Trading Intensity and Market Quality

Trading intensity. To measure trading intensity, I focus on market shares, trading volume, trade count, and trade size. I calculate these measures per day and per stock for the individual order books of the LSE, Chi-X, BATS, and Turquoise as well as for the consolidated order book of all four markets.[6] I aggregate the data either on 15-minute or daily intervals, depending on the scope of my analysis. For instance, daily (15-minute) market shares are based on daily (15-minute) trading volume of a stock (in GBP) on a certain trading venue compared to the rest. Trade count is defined as the average num-

[6]Figure 4.1 explains how I create the consolidated order book.

ber of daily (15-minute) trades per stock for each trading venue. Trade size represents the average daily (15-minute) amount of British Pounds per trade.

Market quality. I measure market quality by calculating quoted spreads, quoted spreads at trade, effective spreads, realized spreads (5 and 15 minutes), price impacts (5 and 15 minutes), and order book depth at best prices and three ticks behind best prices. These measures are also calculated for the individual order books of the LSE, Chi-X, BATS, and Turquoise as well as for the consolidated order book of all four markets.[7]

The most common measure for liquidity is the quoted spread. As a rule of thumb, the wider the quoted spread, the less liquid is an instrument. Quoted spreads are calculated as a proxy of trading costs for each trading venue on an individual order book level. Let $a_{i,t}$ be the ask price for an instrument i at time t and $b_{i,t}$ the respective bid price. $m_{i,t}$ denotes the mid quote, then the relative quoted half spread ($qspread_{i,t}$) in basis points is calculated as follows:[8]

$$qspread_{i,t} = (a_{i,t} - b_{i;t})/(m_{i,t} * 2) * 10{,}000 \tag{4.2}$$

This measure is based on a quote-to-quote process that is characterized by every price or volume update and each trade during the trading day. Then, quoted spreads are aggregated on a daily (15-minute) per instrument basis and averaged per trading venue. To avoid some of the noise of tick-by-tick data, all liquidity measures are winsorized at the 1.0% level and the 99.0% level. I further calculate quoted spreads at trades, which capture liquidity represented through the best bid and ask at the time of execution.

However, quoted spreads only serve as a liquidity proxy for relatively small order sizes. If a comparatively larger order is executed in the market, it most likely consumes more

[7] Effective spreads, realized spreads, and price impacts further explain the necessity of calculating the consolidated order book.

[8] The formula calculates the quoted *half* spread. It implies a buy or a sell of an investor instead of a round-trip (buy and sell), i.e., an investor only has to pay half of these implicit transaction costs if he buys or sells. The multiplier *10,000* expresses the aggregation of spreads to basis points. Please note that 100 bps equal 1%.

than the outstanding volume on the first level of the order book and thus the investor will not be able to receive the best bid or ask as execution price. Therefore, I calculate effective spreads, which measure a market participant's actual implicit costs when his incoming market order trades against more than one limit order.[9]

I use the standard Lee and Ready (1991) algorithm to estimate trade direction (buy or sell) as proposed by Bessembinder (2003).[10] Using the variables from above and let $p_{i,t}$ be the execution price, then the effective half spread ($espread_{i,t}$) is defined as:

$$espread_{i,t} = D_{i,t} * ((p_{i,t} - m_{i,t})/m_{i,t}) * 10{,}000 \tag{4.3}$$

where $D_{i,t}$ denotes the trade direction with -1 for marketable sell and +1 for marketable buy orders. Effective spreads also capture institutional features of trading venues like hidden liquidity or market depth. For example, iceberg-orders that only display a fraction of total trading volume and completely hidden limit orders are available on the LSE, Chi-X, BATS, and Turquoise.[11] Effective spreads are usually equal to or larger than the second liquidity measure, quoted spreads at trades. However, they might be smaller if trading venues feature hidden liquidity and there are a reasonable number of trades executed inside the spread.

I further investigate the individual components of effective spreads according to Glosten (1987), i.e., I decompose effective spreads into realized spreads and price impacts. Realized spreads can be interpreted as the gross profit of liquidity suppliers. Price impacts represent the adverse selection component which measures the costs of trading against a market participants with superior information (Glosten, 1987, p. 1295). The relationship between effective spread, realized spread, and price impact is based on simple arithmetics and can be formalized as follows:

[9]Quoted and effective liquidity may often differentiate substantially.

[10]Following Lee and Ready (1991), I infer trade direction from the trade price position relative to the prevailing quotes and historical prices. Basically, the algorithm checks whether a trade has been executed above or below the midpoint of the last bid-ask quotation.

[11]Fully hidden orders are available at the LSE starting from December 2009. Therefore, I clean the data for inside the spread executions before the introduction of this order type.

$$espread_{i,t} = rspread_{i,t} + pimpact_{i,t} \tag{4.4}$$

In order to capture liquidity provider revenues, I assume that liquidity providers are able to close their position at the quoted midpoint 5 minutes (15 minutes) after the trade. Let $m_{i,t+x}$ denote the mid quote with x = {5, 15} minutes, then the realized half spread is defined as:

$$rspread_{x,i,t} = D_{i,t} * ((p_{i,t} - m_{i,t+x})/m_{i,t}) * 10{,}000 \tag{4.5}$$

The price impact provides an indication of the information content of a trade. It captures the costs of liquidity demanders that arise in the presence of asymmetric information. Traders with superior information will buy when a price is set too low and sell vice versa. Trading against an informed trader thus results in an adversely selected loss. To compensate for informed trading, liquidity suppliers charge a fee on every transaction which is supposed to minimize this expected loss. Using the same variables, I calculate 5-minute and 15-minute adverse selection components of effective spread as follows:

$$pimpact_{x,i,t} = D_{i,t} * ((m_{i,t+x} - m_{i,t})/m_{i,t}) * 10{,}000 \tag{4.6}$$

The calculation of *effective spreads*, *realized spreads*, as well as *price impacts* needs a reference price that is usually the midpoint of the best quoted bid and ask (see formulas above).[12] Considering these measures only in a single market is not problematic. Yet, my analysis covers competition for order flow in four different markets. A comparison between the four markets is only possible if I calculate the consolidated order book of all four markets. The consolidated order book allows me to determine the midpoint of

[12] Barclay et al. (2003) also use the midpoint of best prices as reference price.

the best quoted bid and ask of the LSE, Chi-X, BATS, and Turquoise, which serves as a reference price.[13]

After all, liquidity is not only defined by narrow quoted and effective spreads which reduce implicit trading costs. Another major market quality attribute is the *"thickness"* of an order book which is related to the volume present at each level of the order book. Therefore, I use order book depth data to compute quoted volume at different order book levels in the individual order books. Let $B_{i,t}$ be the corresponding volume at the bid and $A_{i,t}$ at the ask, then the quoted half depth ($depth_{x,i,t}$) in British Pounds is computed as follows:

$$depth_{x,i,t} = \sum_{x=1}^{X} (B_{x,i,t} + A_{x,i,t}) / (2 * 100) \tag{4.7}$$

where X = {1, 3} characterizes the order book level. $depth_{1,i,t}$ is the average half quoted volume at the best bid and ask, while $depth_{3,i,t}$ incorporates the quoted volume up to three ticks behind best prices.

4.2.3 Price Discovery

Besides liquidity and volume order book depth, there are also other important factors that are connected to market quality. Many scholars argue that the price of a stock itself or better said, the information of a price which is conveyed to the market, represents such an important factor of market quality. For instance, Huang (2002) points out that «[...] *price leadership, or price discovery, which is accomplished by timely submission of informative quotes [...]*» is an important dimension of market quality. In Section 4.2.2, I presented price impacts as one indication for the information content of a trade. But this measure is only indirectly linked to other trading venues over the calculation of a consolidated order book. Yet, there are other models which may measure price

[13] By creating a consolidated order book, I assume that market participants are able to monitor quotes at all four markets. This assumption is logical, given the modern SOR technologies that most institutional market participants use, compare Section 3.3.

discovery – which is the enclosure of new information into a stock price – in a more direct relationship, i.e., not connected to a spread decomposition or a consolidated order book.

With an increasing number of trading venues that form stock prices, it is of particular interest to see which trading venue conveys new information to the market first, i.e., where prices move "first". Hasbrouck (1995) creates a measure which investigates price leadership – based on quote updates – of a single market in a fragmented market environment. Several other scholars have relied on this measure to determine where buyers and sellers contribute to efficient price discovery (Goldstein et al., 2008; Hendershott and Riordan, 2009; Riordan et al., 2011).

The main idea behind this measure is based on findings of Garbade et al. (1979), Garbade and Silber (1979), and Garbade and Silber (1983) who argue that prices in fragmented markets share a common implicit efficient price. Based on this assumption, Hasbrouck (1995) states that actual transaction prices «[...]*are determined by a bid-ask spread component or an autoregressive adjustment component. An appealing characteristic of a common implicit efficient price is that it supports the economic intuition that, subject to transaction costs, the securities traded in different markets are linked by arbitrage or short-term equilibrium considerations.*» (Hasbrouck, 1995, p.1176). Based on this implicit efficient price that is common to all markets, it is of interest to identify the sources of variation in this efficient price which can be attributed to different markets. The amount of innovation that a market contributes to overall price discovery is defined as *the proportion of the efficient price innovation variance*, which represents the *"information share"* of a market. From an econometrical perspective, the approach of Hasbrouck (1995) relies on co-integration which is used to explain the connection of multiple price series of a stock in various markets through the common component which they share.

Hasbrouck (1995) argues that prices of an individual stock p_t^j traded on multiple trading venues j are integrated and thus non-stationary. Yet, he states that a linear combination of these prices may be stationary. Under the assumption that all prices follow a random walk, they are integrated of order *1* and $\triangle p_t$ is a stationary process. In order to model the implicit efficient price, I use prevailing midpoints of the consolidated order book

m_t. This efficient price is influenced by price innovation updates coming from the four different markets. Therefore, I model the current price as a combination of the implicit efficient price and a price vector $p_t = [p_t^{LSE}, p_t^{ChiX}, p_t^{BATS}, p_t^{TQ}]'$ where each p_t^j refers to the same stock:

$$p_t = m_t + [\epsilon_t^{LSE}, \epsilon_t^{ChiX}, \epsilon_t^{BATS}, \epsilon_t^{TQ}]' \tag{4.8}$$

and m_t is supposed to follow a random walk:

$$m_t = m_{t-1} + \omega_t, \tag{4.9}$$

where ω_t follows a white noise process with $E(\omega_t) = 0$, $E(\omega_t^2) = \sigma_t^2$, and $E(\omega_t \omega_s) = 0$ for $t \neq s$. The moving average representation for the price vector $\triangle p_t$ can be written by using a vector moving average (VMA) model:

$$\triangle p_t = \epsilon_t + \sum_i \psi_i \epsilon_{t-i} \tag{4.10}$$

$\epsilon_t = [\epsilon_t^{LSE}, \epsilon_t^{ChiX}, \epsilon_t^{BATS}, \epsilon_t^{TQ}]'$ is a (4×1) vector innovation process with $E(\epsilon_t) = 0$ and a variance matrix $Var(\epsilon_t) = \Omega$. The ϵ_t components represent the new information which is incorporated in the corresponding market $(LSE, ChiX, BATS, TQ)$ and the ϵ_{t-i} is a (4×4) matrix. This means that the (i,j)-element of ϵ_t measures a one unit change of ϵ_t upon $\triangle p_t$, where $i,j \in [LSE, ChiX, BATS, TQ]$

In equations (4.8) and (4.9), I show that a an observed price can be decomposed into a random walk component and a covariance-stationary error term. According to this, the variance of the random walk component is:

$$\sigma_t^2 = \Psi \Omega \Psi' \tag{4.11}$$

where Ω is the $(n \times n)$ covariance matrix of the innovations and Ψ is a polynomial in the lag operator. This means that the random walk variance reflects the individual contributions from all four markets as follows:

$$\sigma_t^2 = A \begin{pmatrix} \sigma_{LSE}^2 & \sigma_{LSE,ChiX} & \sigma_{LSE,BATS} & \sigma_{LSE,TQ} \\ \sigma_{ChiX,LSE} & \sigma_{ChiX}^2 & \sigma_{ChiX,BATS} & \sigma_{ChiX,TQ} \\ \sigma_{BATS,LSE} & \sigma_{BATS,ChiX} & \sigma_{BATS}^2 & \sigma_{BATS,TQ} \\ \sigma_{TQ,LSE} & \sigma_{TQ,ChiX} & \sigma_{TQ,BATS} & \sigma_{TQ}^2 \end{pmatrix} A' \tag{4.12}$$

where $A = [\Psi^{LSE}, \Psi^{ChiX}, \Psi^{BATS}, \Psi^{TQ}]$. In case that the covariance matrix is diagonal (when $\sigma_{i,j}^2 \neq 0$) for $i = j$, the contribution of each market to the price discovery process can be clearly identified. The larger the relative size of these contributions, the more a market contributes to price discovery and is thus of higher importance with regard to efficient prices. This contribution, known as information share of the jth market is defined as follows:

$$InfoShare_j \equiv \frac{\Psi_j^2 \Omega_{jj}}{\Psi \Omega \Psi'} \tag{4.13}$$

where $j \in \{LSE, ChiX, BATS, TQ\}$. The contribution of market j to price discovery is represented by $\Psi_j^2 \Omega_{jj}$ and $\Psi \Omega \Psi'$ represents the variance of the random walk component of stock prices representing the total price discovery.[14] To determine upper and lower bounds that minimize or maximize the contribution of each trading venue in the price discovery process, I follow Hasbrouck (1995).

I calculate information shares for each trading venue per day and per stock. In order to determine the contribution of each trading venue to price discovery, I calculate and compare the mean of upper and lower bounds across all four venues. By construction, information shares sum up to 100%. Figure 4.3 displays 10-day moving averages of information shares of the LSE, Chi-X, BATS, and Turquoise. It is clearly visible, that the LSE and Chi-X contribute most to efficient price discovery during 2009. However, prices on the LSE continuously lose information shares, while Chi-X gains information shares over the entire observation period.

[14]It is possible that the contemporaneous midpoint of the different trading venues can be equal, which would mean that midpoints could be correlated. This would infer that Ω is not diagonal.

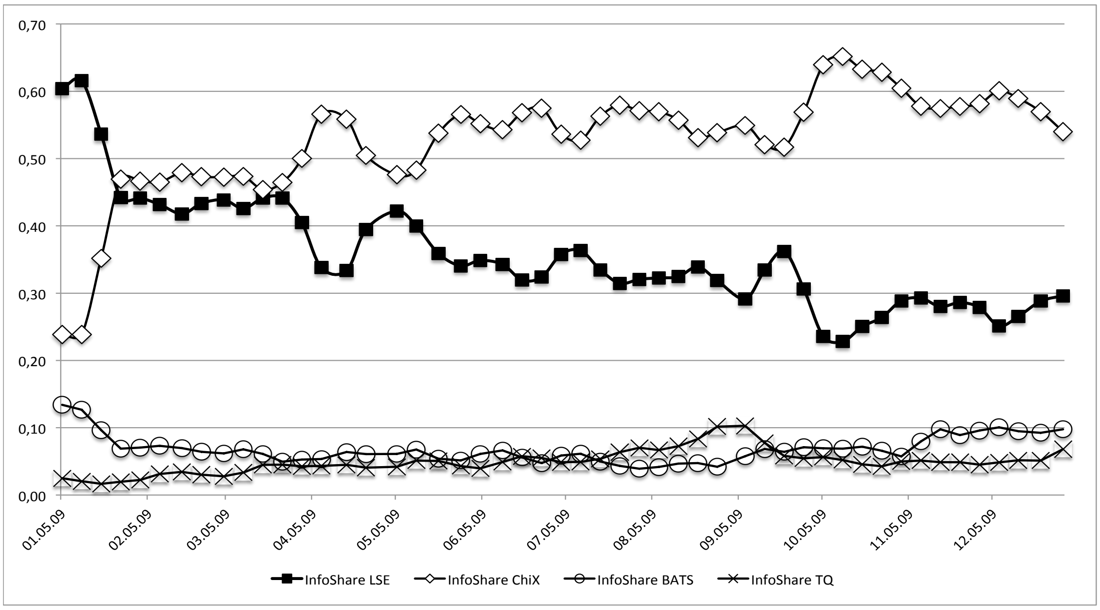


FIGURE 4.3: ***Hasbrouck (1995) Information Shares.*** *The figure displays 10-days moving average information shares of the LSE, Chi-X, BATS, and Turquoise. Per definition, information shares add up to 100%.*

4.2.4 Market Making

In Chapter 6, I address the changes in daily trading intensity on various trading platforms in the light of technological changes and the emergence of HFT. Apparently, HFT trading activity is particularly interesting for MTFs which try to concentrate on these new market participants by offering various benefits, e.g. special fee models and ultra fast order execution. Therefore, HFT accounts for a large share of trading volume on MTFs. The high speed environment of MTFs allows HFT to quickly provide and consume liquidity on various platforms almost in the same instant. This environment is very suitable for HFT trading strategies which are often based on passive, liquidity providing orders to manage their target inventory. HFT act thus as modern multi-venue market makers (Menkveld, 2011b; Kirilenko et al., 2011).

However, even if HFT may act as modern market makers they do not have to comply with the regulatory requirements such as traditional market makers, i.e., they are not obliged to provide liquidity according to the rule book of a traditional exchange. Thus, liquidity provision by HFT may not be granted as stable over time which apparently might become a problem for other market participants. In the context of my analysis in Chapter 6, I address these issues and analyze a change in market participants' order routing behavior when market making becomes difficult and thus might be costly.

Similar to Boehmer et al. (2013), I create a proxy for difficult market making days which is based on daily returns. From a market maker perspective, the job of providing liquidity is easiest when buyers and sellers arrive with the same probability. The market maker's inventory risk is thus easy to handle. However, market makers' inventory risk increases substantially if a trading day becomes biased to either the buy or the sell side. For instance, if a trading day exhibits an order imbalance towards the sell side, the price of an instrument is most likely to fall. In this scenario, the market maker has to buy from potential sellers which thus adds to his inventory. However, along with his increasing inventory, the book value of its inventory decreases due to the falling price. Typically, he would try to have a zero position at the end of the trading day. Yet, if he decides to close his inventory position at the prevailing low price this would culminate in realized loss. Alternatively, he may take an overnight position with the attached risk and wait until the next day when the price might move in the other direction. Yet, his loss increases further if the negative order imbalance prevails on the second or even third day as well. The same accounts for a long scenario of course where the market maker has to deal with a short inventory position.

Following this argumentation, I create a proxy for difficult market making days for each individual stock in my sample. The proxy has either the value 1 if representing a difficult market making day or 0 otherwise. A difficult market making day is characterized by the daily return having the same sign as the return of the previous day. I thus assume that a trading day exhibits a positive or negative order imbalance. Consequently, I identify all of these days in my sample period on each individual trading venue. Additionally, I disregard difficult market making days which only exhibit small changes in returns. These days probably do not cause severe problems for market makers' liquidity provision. For this reason, I only consider days where the cumulative return on the second day exceeds the monthly average return in a stock by at least two standard deviations.

Table 4.1 summarizes simple statistics of difficult market making days on all trading venues – combined and individual – for the full yearly sample as well as Q1 and Q4. On each trading venue, I check on an individual stock level whether the return on a trading day qualifies as my desired proxy. Since returns and volatility of a stock may deviate on the individual trading venues this may lead to diverging dummy classifiers on the different trading venues. For example, a trading day on Chi-X may qualify as a difficult market making day, while on the LSE it is considered as a regular day. Therefore, Table 4.1 displays difficult market making days on the single trading venues, as well as combined category *"All"*. This category includes all dummies that have been classified as a difficult market making day on any of the four trading venues. My overall sample covers 16,836 observations (244 trading days for each single stock of my 69 stock sample). Q1 and Q4 cover 4,140 (60 trading days) and 4,209 (61 trading days) observations, respectively.

Statistics indicate that difficult market making days are on average evenly distributed over time: In the yearly sample, roughly 3.7% of the observations on all trading venues qualify as a difficult market making day. This ratio is quite similar for Q1 and Q4 with 3.3% and 3.6%, respectively. Over the entire year, Chi-X exhibits in sum the largest number of difficult market making days, while in Q1 and Q4 Turquoise and the LSE lead, respectively.

Table 4.2 displays correlation statistics for difficult market making days on the different trading venues for the three periods. The table indicates that difficult market making days are highly correlated on all four trading venues, in Q4 even a bit more than in Q1. Because dummies are evenly distributed over time and highly correlated between trading venues, I use the combined proxy – category *"All"* in Table 4.1 – in my empirical analysis in Chapter 6. In total 616 trading days have been identified as difficult market making days where consequently inventory risk is higher.

TABLE 4.1: ***Descriptive statistics: Difficult market making days on the LSE, Chi-X, BATS, and Turquoise.*** *The table displays simple statistics of dummy variables of difficult market making days across all stocks on the four trading venues. A trading day is considered as a difficult market making day if the daily return of the stock has the same sign as the return of the previous day. Additionally, the cumulative return on the second day needs to exceed the monthly average return in a stock by at least two standard deviations. The category "All", includes dummy variables of all trading venues, i. e. if a trading day is identified as a difficult market making day on any of the four platforms it is included into "All".*

Full Sample Statistics (N=16,836)		
Venue	Mean	Sum
All	0.037	616
LSE	0.032	544
ChiX	0.032	545
BATS	0.032	533
TQ	0.032	538
Q1 Statistics (N=4,140)		
Venue	Mean	Sum
All	0.033	137
LSE	0.026	108
ChiX	0.027	112
BATS	0.027	112
TQ	0.028	117
Q4 Statistics (N=4,209)		
Venue	Mean	Sum
All	0.036	152
LSE	0.034	141
ChiX	0.032	136
BATS	0.031	131
TQ	0.033	138

TABLE 4.2: ***Correlation: Difficult market making days on the LSE, Chi-X, BATS, and Turquoise.***

Pearson correlation coefficients Full Sample					
	dMM_all	dMM_lse	dMM_chi	dMM_bats	dMM_tq
dMM_all	1	0.93766	0.93855	0.92782	0.93231
		<.0001	<.0001	<.0001	<.0001
dMM_lse		1	0.92545	0.86941	0.88654
			<.0001	<.0001	<.0001
dMM_chi			1	0.91741	0.87897
				<.0001	<.0001
dMM_bats				1	0.85201
					<.0001
dMM_tq					1
Prob > |r| under H0: Rho=0					

Pearson correlation coefficients Q1					
	dMM_all	dMM_lse	dMM_chi	dMM_bats	dMM_tq
dMM_all	1	0.88466	0.90136	0.90136	0.92183
		<.0001	<.0001	<.0001	<.0001
dMM_lse		1	0.92545	0.86941	0.88654
			<.0001	<.0001	<.0001
dMM_chi			1	0.91741	0.87897
				<.0001	<.0001
dMM_bats				1	0.85201
					<.0001
dMM_tq					1
Prob > |r| under H0: Rho=0					

Pearson correlation coefficients Q4					
	dMM_all	dMM_lse	dMM_chi	dMM_bats	dMM_tq
dMM_all	1	0.96183	0.94405	0.92596	0.95120
		<.0001	<.0001	<.0001	<.0001
dMM_lse		1	0.94417	0.91708	0.95187
			<.0001	<.0001	<.0001
dMM_chi			1	0.95763	0.93212
				<.0001	<.0001
dMM_bats				1	0.91969
					<.0001
dMM_tq					1
Prob > |r| under H0: Rho=0					

Chapter 5

Market Quality & Intraday Patterns in Fragmented Markets

"The open and the close of trading in a stock market that is open during the day and closed overnight seem to be natural candidates for investigation. While the information on which the asset prices are based evolves continuously over the entire period, there is an abrupt change from a regime of continuous trading to one of zero trading. How does this affect trading behavior at the transition points, namely open and close?"

Brock and Kleidon (1992)

Chapter Overview. This chapter empirically addresses the influence of increased order flow fragmentation on overall market quality in the UK equity market. In a first part, I address changes of market quality over time. The second part contains an intraday analysis of various market quality measures that investigate the competitive behavior of the LSE, Chi-X, BATS, and Turquoise within a trading day. I also compare these intraday patterns over time to see whether there are significant changes in the patterns themselves or in the position of a particular market.

5.1 Introduction

THE introduction of MiFID in 2007 has significantly altered European equity markets as it allowed alternative trading platforms (MTFs) to compete with traditional exchanges for equity order flow. MTFs concentrated on the heterogeneous desires of investors, such as trading speed, anonymity, or alternative fee schedules. This increased the competitive pressure on traditional national exchanges such as the London Stock Exchange (LSE) or Deutsche Boerse. As a consequence, order flow and liquidity became fragmented across trading venues. (See Chapter 2 for a detailed discussion about MiFID and the UK equity market development.)

Market statistics in Section 2.2 underline this development and show that trading has fragmented strongly since the introduction of MiFID. UK blue chip stocks are the most fragmented European equities. For example, LSE's market share in FTSE 100 constituents decreased continuously from close to 100% in 2007 to just 43% in June 2011.[1] It is important to note that there has been a real loss in market share at the LSE during my 2009 observation period, i.e., new trading venues have not added additional trading volume to the overall market which would decrease LSE market share relatively, but they have actually taken it away from the LSE. Overall, absolute trading volume in all FTSE 100 constituents at the LSE decreased by roughly 45% from December 2008 (1.6 trillion GBP) to December 2009 (890 billion GBP). The number of trades decreased during the same period by roughly 17% from 128 million to 106 million trades (London Stock Exchange, 2009c).

The question whether order flow and liquidity should be concentrated geographically started an important debate which has been discussed in detail by various authors empirically (e.g., Easley et al., 1996; Battalio et al., 1997) and theoretically (e.g., Pagano, 1989b,a; Chowdhry and Nanda, 1991). Intuitively, the probability of order execution should decline if demand and supply are separated across various platforms which speaks against the intention of MiFID to increase competition

[1] For detailed statistics on European equity market fragmentation, see `http://fragmentation.fidessa.com`.

– and thus fragmentation – in European equity markets. However, increased intermarket competition may reduce the monopoly power of traditional exchanges and thus decrease transaction costs and inspire trading venues to develop new services (European Commission, 2010). The relationship between market fragmentation and its effects on market quality are thus ambiguous. Another aspect that mitigates potential negative effects of market fragmentation nowadays, is connected to modern information and communication technology. The existence of high-speed internet and smart order routing technologies significantly reduce search and monitoring costs as they actively contribute to a virtual integration of trading venues, even if they are spatially apart. (See Chapter 3 for a detailed literature overview which discusses the effects of market fragmentation, intraday competition, and the influence of technology on market quality.)

Tick-by-tick order book data of the LSE and the three largest European MTFs (Chi-X, BATS, and Turquoise) allow me to address this complex scenario of a multiple fragmented trading environment from January until December 2009. I analyze the influence of market fragmentation and increased competition on trading intensity and market quality. I deliberately investigate this relationship from two perspectives: (1) over time and (2) intraday.

Firstly, I study changes of trading intensity and market quality measures in fragmented markets over time. I find evidence that fragmentation increases significantly during 2009. Along with increasing fragmentation between the LSE and the three MTFs, I find no support speaking in favor of a deterioration of market quality which would point out that a centralization of trading is preferable. Contrarily, market quality seems to improve on all trading venues. Especially MTFs exhibit very high liquidity measures which emphasize the strong competition between MTFs and the traditional exchange. Partially, effective spreads are even smaller on MTFs than on the LSE which indicates larger liquidity on MTFs.[2]

Secondly, I address intraday competition between trading venues and investigate

[2] However, this result may stem from hidden liquidity, e.g. iceberg order or hidden limit orders, which were available on MTFs during the whole year of 2009 while the LSE introduced hidden limit orders not before December 2009. Please compare Section 2.2 for further details.

whether spreads, trading volume, market shares, and informed trading concentrate on a single platform during specific periods within a trading day.[3] Overall, I observe that intraday patterns of trading volume, market shares, quoted spreads, and price impacts converge from Q1 to Q4 across trading venues, i.e., measures develop with a higher similarity across trading venues over time, which indicates a maturing market. I find that increasing market fragmentation does not significantly change intraday patterns over time, with the exception of quoted spreads on Turquoise. Within the trading day, my data provide evidence that market shares shift away from the regulated market to MTFs after market opening and then back before market closing. This result suggests that market participants route their orders preferably to the LSE in times of increased volatility and price uncertainty (e.g., Foster and Viswanathan, 1993). Potentially, they favor the price formation process and price quality at the regulated market during these periods.[4]

Quoted spreads are predominantly crude reversed J-shaped on all trading venues which means that liquidity increases throughout the trading day. For trading volume, I find opposing patterns for the LSE and MTFs. While LSE trading volume follows a U-shape, indicating already high trading intensity at market opening (in line with e. g. , Foster and Viswanathan (1993) and Werner and Kleidon (1996)), trading volume at MTFs starts at lower levels and increases not before the second half of the trading day. On all trading venues, I find the inverse relationship between decreasing spreads (increasing liquidity) and growing volume over the trading day, also documented by McInish and Wood (1992) and Cai et al. (2004). Price impacts, which indicate informed trading (see 4.2.2), decrease on all platforms during the trading day which might be connected to a decreasing arrival of news over the trading day (Klussmann and Hautsch, 2011).

[3]Please refer to Section 4.1 for a detailed description of my data sample and my observation periods for this chapter.

[4]I will address this relationship in my second empirical analysis in Chapter 6, to see whether this finding is mainly an intraday effect or whether the this relationship holds also over time.

5.2 Interday Analysis

5.2.1 Descriptive Statistics

I calculate various trading intensity and market quality measures per day and per stock for the individual order books of the LSE, Chi-X, BATS, and Turquoise as well as for the consolidated order book of all four markets, as outlined in Section 4.2.2.[5]

Table 5.1 reports descriptive statistics of trading intensity and market quality measures across all 69 stocks of my sample for Q1 2009. I report standard deviations of each measure in parenthesis. I also test mean differences between the LSE and each MTF for statistical significance.[6] Standard errors with "***" denote statistical significance at the 1% level and "**" at the 5% level, and "*" at the 10% level. Markets are fragmented with a LSE market share of 72.31% of total trading volume. Chi-X captures 16.74% of trading volume, BATS 2.47%, and Turquoise 8.48%. The largest trades are executed on the LSE with an average trade size of 10,304 GBP. Trade sizes are in general smaller on MTFs with Turquoise showing the largest trade size with 7,000 GBP compared to Chi-X and BATS with 6,373 GBP and 5,302 GBP, respectively.

Average daily quoted spreads at the LSE are smallest with 7.38 bps followed by Chi-X with 9.80 bps. BATS and Turquoise show wider average daily quoted spreads with 12.91 bps and 20.22 bps. This indicates less liquidity on these two trading platforms compared to the LSE and Chi-X. Interestingly, average daily quoted spreads at trade are considerably smaller than daily quoted spreads on all platforms. This suggests that market participants actively monitor quotes and tend to buy or sell when it is relatively cheap to do so, i.e., when spreads are narrow.

Effective spreads represent the cost that is actually paid by a liquidity demander for a transaction. On the LSE, a liquidity demander has to pay on average 4.90 bps during Q1. Interestingly, effective spreads are smaller on Chi-X with 4.81 bps and Turquoise

[5] Please refer to Sections 4.1 and 4.2.2 for computational details on the consolidated order book or the trading intensity and market quality measures.

[6] For the mean difference tests, I estimate standard errors by using the methodology according to Thompson (2011).

TABLE 5.1: ***Descriptive statistics: Trading ntensity and liquidity measures for Q1 2009.*** *The table presents average trading intensity and market quality measures over all 69 stocks during Q1. Market shares are based on daily trading volume (Volume) in British Pounds (GBP). All spread measures are reported in basis points. The Quoted Spread is calculated on a tick-by-tick basis per stock, the Quoted Spread Trade is calculated trade-by-trade. Realized Spread and Price Impact are reported for both 5 and 15 minute benchmarks relative to the midpoint of the consolidated order book. Depth1 is half the quoted depth at the best bid and ask. Depth3 includes the total quoted volume three ticks behind best prices. Standard deviations are reported in parenthesis. Mean differences between the LSE and each MTF are tested for statistical significance using Thompson (2011) standard errors with '***' denoting statistical significance at the 1% level and '**' at the 5% level, and '*' at the 10% level.*

	LSE	**Chi-X**	**BATS**	**TQ**
Market Shares [%]	72.31%	16.74%***	2.47%***	8.48%***
	(7.27%)	(5.32%)	(1.30%)	(4.72%)
Volume [1,000 GBP]	43,536	10,763***	1,625***	4,597***
	(54,029)	(13,988)	(2,260)	(4,971)
Trade Count [No]	3,527	1,362***	247***	572***
	(2,518)	(1,046)	(223)	(404)
Trade Size [GBP]	10,304	6,373***	5,302***	7,000***
	(5,191)	(3,376)	(3,012)	(3,972)
Quoted Spread [bsp]	7.378	9.804***	12.913***	20.217***
	(4.162)	(9.467)	(24.512)	(89.838)
Quoted Spread Trade [bsp]	5.625	6.232	7.695***	10.328***
	(3.293)	(3.532)	(3.977)	(17.606)
Effective Spread [bsp]	4.909	4.811**	5.164***	4.189***
	(2.938)	(2.886)	(3.104)	(2.9583)
Realized Spread 5 [bsp]	-0.248	-0.136*	1.351***	-0.280
	(1.938)	(2.502)	(4.955)	(4.327)
Realized Spread 15 [bsp]	0.183	0.127	1.044***	-0.186*
	(3.140)	(3.924)	(8.952)	(7.042)
Price Impact 5 [bsp]	5.190	4.955***	3.840***	4.489***
	(3.160)	(3.350)	(5.273)	(4.328)
Price Impact 15 [bsp]	4.778	4.700	4.156***	4.400**
	(4.034)	(4.611)	(9.285)	(7.066)
Depth1 [GBP]	29,487	29,812	20,300***	18,269***
	(30,674)	(30,674)	(21,776)	(15,210)
Depth3 [GBP]	102,326	124,319**	69,358***	58,858***
	(133,551)	(133,551)	(72,050)	(53,398)

with 4.18 bps. BATS shows on average the largest effective spread with 5.16 bps. Smaller effective spreads – calculated with the midpoint from the consolidated order book – compared to quoted spreads at trade from single order books suggest that investors could economically benefit from trading on all four venues simultaneously. This finding is most likely an important reason for the existence of SOR technologies

which monitor quotes and trades on different markets. Typically, effective spreads and quoted spreads at trade are relatively close. In the case of Turquoise, I observe that average daily effective spreads are lowest compared to the LSE, Chi-X, and BATS while Turquoise shows the largest discrepancy between effective spreads and quoted spreads at trade among all trading venues. This result is in line with Riordan et al. (2011) who provide evidence that Turquoise's small effective spreads are considerably influenced by overall market conditions and the small number of trades on Turquoise. Another possibility of smaller effective spreads on Chi-X or Turquoise during Q1 may be connected to hidden liquidity. While hidden limit orders were available on all MTFs during the whole year of 2009, the LSE introduced hidden limit orders not before December 2009.[7]

5 and 15-minute realized spreads deliver mixed results across platforms. BATS is the only trading venue where investors benefit from supplying liquidity with 1.35 bps given that they close their position 5 minutes after the trade. For the 15-minute interval, all trading venues except Turquoise show positive realized spreads, which indicates that investors would benefit from supplying liquidity.

Liquidity demanders with superior price information seem to be most active on the LSE, as 5-minute and 15-minute price impacts are highest on this platform (5.19 bps on the LSE, compared to 4.95 bps on Chi-X, 3.84 bps on BATS, and 4.49 bps on Turquoise, for 5-minute price impacts). Put differently, price impacts suggest that the risk of being adversely selected from a trader with superior information is highest on the LSE for Q1, 2009.

On the LSE, average order book depth at level one is 29,487 GBP and 102,326 GBP for the cumulated depth three ticks behind best prices. Compared to the LSE, depth is slightly higher on Chi-X but significantly lower on BATS and Turquoise.

[7] See Section 2.2 for further details.

5.2.2 Changes over Time

I compare Q1 and Q4 of 2009 in order to analyze differences in trading intensity and market quality measures over time and across trading venues along with the level of market fragmentation. My regression model is defined per trading day t and per stock i as follows:

$$measure_{i,t} = \alpha_0 + \beta_1 \, quarter_{i,t} + \sum \gamma_j controls_{i,t} + \epsilon_{i,t} \tag{5.1}$$

where my dependent variables $measure_{i,t}$ are different trading intensity and market quality measures as introduced in Chapter 4. The variable of interest, $quarter_{i,t}$, is a dummy variable which takes the value 1 for Q4 and is 0 otherwise. It captures differences between Q1 and Q4 of 2009 which are reported by the coefficient β_1. Similar to Hendershott and Moulton (2011), I control for market conditions between both observation periods. Therefore, I include the logarithm of daily market capitalization, the average daily realized volatility, the logarithm of daily closing prices, and firm dummy variables. To estimate robust standard errors, I follow Thompson (2011).[8]

Table 5.2 depicts differences between quarters and trading venues relative to the LSE. The first column of each trading venue (Q4 - Q1) shows differences in trading intensity and market quality measures between Q1 and Q4 of 2009. The second column (Venue - LSE) reports changes of each trading venue over time relative to the LSE, which are obtained by combining results from the quarterly differences. I present t-statistics below the regression estimates in italic letters. "***" denotes significance at the 1% level, "**" at the 5% level, and "*" at the 10% level.

As expected, my regression results confirm that the LSE market share declines significantly by 17.48% between both observation periods. Chi-X and BATS gain significant market shares over time, with 11.99% and 7.57%, respectively. The market share of Turquoise decreases by 2.08% from Q1 to Q4. Trading volume and the number of trades

[8]Clustered standard errors according to Thompson (2011) control simultaneously for correlations in the regression residuals across two dimensions. In my data panel, residuals might be correlated across sample firms (firm effect) and across time (time effect). Clustering for those two dimensions allows me thus to obtain robust standard errors. For details on the methodology, see Thompson (2011).

TABLE 5.2: ***Interday regression results: Trading intensity and liquidity measures.*** *I compare 69 stocks listed on the LSE and in the FTSE 100. The first period contains trading days between January 5 to March 31, 2009 (Q1) and the second period between October 1 to December 30, 2009 (Q4). The final sample contains 69 stock pairs. I use the regression model presented in Equation 5.1 to test for differences (1) between the observation periods (Q4-Q1) and (2) for trading venue differences relative to the LSE (Venue-LSE) per trading day t and per stock i. I use Thompson (2011) clustered standard errors. t-statistics are presented below the regression estimates in italic letters. '***' denotes significance at the 1% level, '**' at the 5% level, and '*' at the 10% level.*

	LSE	**Chi-X**		**BATS**		**TQ**	
	Q4-Q1	Q4-Q1	ChiX-LSE	Q4-Q1	BATS-LSE	Q4-Q1	TQ-LSE
Market Shares	-17.48%***	11.99%***	29.46%***	7.57%***	25.04%***	-2.08%***	15.40%***
	-33.06	*20.59*	*29.50*	*21.09*	*34.89*	*-4.13*	*19.79*
Volume (1,000 GBP)	-14,107***	3,732***	17,840***	3,853***	17,961***	-1,793***	12,315***
	-5.78	*3.80*	*7.15*	*7.26*	*6.50*	*-4.15*	*5.76*
Trade Count	-980***	543***	1,522***	614***	1,594***	-15	965***
	-7.46	*6.26*	*10.94*	*10.75*	*10.25*	*-0.36*	*7.65*
Trade Size (GBP)	932***	264	-669***	-614***	-1,546***	-2,417***	-3,349***
	2.73	*1.15*	*-3.21*	*-2.89*	*-6.70*	*-6.08*	*-10.07*
Quoted Spread	-0.719***	-3.231***	-2.512***	-2.337*	-1.618	-4.990	-4.271
	-3.15	*-4.88*	*-3.87*	*-1.82*	*-1.27*	*-1.27*	*-1.51*
Quoted Spread Trade	-0.674***	-1.974***	-1.300***	-2.895***	-2.221***	-0.587	0.087
	-3.09	*-5.44*	*-3.44*	*-8.25*	*-5.83*	*-0.60*	*0.09*
Effective Spread	-0.781***	-0.706***	0.075	-1.289***	-0.508***	-0.690***	0.091
	-4.21	*-3.82*	*1.41*	*-6.86*	*-8.31*	*-3.61*	*0.92*
Realized Spread 5	-0.145	0.182	0.327***	-1.140***	-0.995***	0.073	0.218
	-1.37	*1.50*	*4.77*	*-4.55*	*-3.67*	*0.39*	*1.47*
Realized Spread 15	-0.298**	0.102	0.399***	-0.617**	-0.319	0.326	0.623***
	-2,14	*0.73*	*3.93*	*-2.41*	*-0.98*	*1.35*	*3.44*
Price Impact 5	-0.643***	-0.903***	-0.260***	-0.162	0.481*	-0.771***	-0.129
	-3.88	*-5.49*	*-2.92*	*-0.65*	*1.88*	*-5.73*	*-1.18*
Price Impact 15	-0.488***	-0.823***	-0.335***	-0.685***	-0.196	-1.017***	-0.529***
	-2.70	*-4.47*	*-3.01*	*-2.24*	*-0.63*	*-5.10*	*-3.03*
Depth1 (GBP)	11,695***	5,031	-6,664***	-2,868	-14,562***	-8,717***	-20,422***
	4.12	*1.19*	*-2.88*	*-1.12*	*-7.77*	*-5.00*	*-7.34*
Depth3 (GBP)	92,502***	61,284***	-31,218**	14,054	-78,448***	-23,412***	-115,973***
	5.78	*2.80*	*-2.34*	*1.34*	*-7.92*	*-3.90*	*-7.49*

decrease on the LSE and Turquoise between Q1 and Q4, while Chi-X and BATS show an increase in trading activity. Average trade size in terms of GBP per trade increases most significantly on the LSE with 932 GBP and slightly on Chi-X with 264 GBP. Trades on BATS and Turquoise become smaller over time with a decrease of -614 GBP and -2,417 GBP, respectively. I assume that this development is connected to clientele effects. MTFs offer economically more beneficial fee schedules to algorithmic and high frequency traders who submit smaller orders at a higher frequency compared to human traders (Hendershott and Riordan (2009)).

For my market quality measures, quoted spreads, quoted spreads at trade, and effective spreads, I find negative coefficients for all trading venues over time, i.e. liquidity improves between Q1 and Q4 on each platform. Quoted spreads decrease between -0.72 bps on the LSE and -5.00 bps on Turquoise. Relative to the LSE, quoted spreads on all MTF improve more over 2009. For example, the difference in quoted spreads between the LSE and Chi-X decreases by -2.51 bps. This means that competition increases overall market quality as MTFs are catching up with the LSE with regard to quoted liquidity. Differences between Q1 and Q4 in effective spreads range between -0.69 bps on Turquoise and -1.29 bps on BATS. Recall that I find even smaller effective spreads on Chi-X and Turquoise than on the LSE during Q1 (see 5.1). Yet, Chi-X could not increase this competitive edge further as the LSE shows a stronger decline in effective spreads from Q1 to Q4 (-0.78 bps).

Results on realized spreads are mixed. While realized spreads decrease significantly on BATS between Q1 and Q4, they do not change significantly on the other trading venues. Price impacts for 5 and 15-minute benchmarks decrease significantly on almost all platforms over time.[9] Relative to the LSE, 5-minute price impacts decrease by -0.26 bps on Chi-X but significantly increase by 0.48 bps on BATS. This result may indicate that – relative to the LSE – the number of market participants with superior information decreases on Chi-X and increases on BATS.

[9]Please recall that realized spreads and price impacts are derived from effective spreads. If effective spreads on all trading venues decrease over time, this is also connected to smaller realized spreads and price impacts. Therefore, the relative shifts of realized spreads and price impacts between the LSE and the MTFs are of higher interest than the absolute shifts.

With regard to order book depth, LSE's order book depth increases significantly by 11,695 GBP on the best bid and ask and 92,502 GBP three ticks behind best prices from Q1 to Q4. MTFs do not exhibit a significant increase in order book depth. Indeed they show rather a contrasting picture. Either their depths increase only little or reduce heavily as it is the case for Turquoise which shows significantly smaller depths by -8,717 GBP on the best level and -23.412 GBP three ticks behind. This result reveals a very important fact which may be also connected to structural differences of the trading venues, or better said to their trading clientele. While LSE's order book becomes "thicker" over time, MTF order books remain as before. This may be connected to the trading clientele on MTFs. Here, HFT is more active. These traders constantly monitor the market, submit smaller orders in general and often cancel orders just a few milliseconds after they have been placed (Hendershott and Riordan, 2009; Breuer and Burghof, 2012). This dimension of liquidity thus reveals that the LSE is more capable of absorbing larger market movements compared to MTFs which may help the LSE to be more resistant for market distortion.

In general and in contrast to theoretical argumentation (Mendelson, 1987; Pagano, 1989b; Chowdhry and Nanda, 1991), I find evidence that increased market fragmentation contributes positively to overall market quality. The regression results show that liquidity measured in terms of quoted spreads and effective spreads increases considerably on the LSE, Chi-X, BATS, and Turquoise between Q1 and Q4. My results also indicate that market participants may benefit from using SOR technologies, as effective spreads (from the consolidated order book) are smaller than quoted spreads at trade (on the individual trading venues). This means that market participants could benefit if they are able to use quotes and prices from all four trading venues. My results also reveal that different developments in depth liquidity measures may be connected to trading clientele effects, as for instance order book depth does not change significantly on MTFs.

5.3 Intraday Analysis

Differences in trading intensity and market quality between trading venues may not only differ over time but may also exhibit intraday variations. By analyzing the latter, I gain insights into the behavior of market participants on each platform. Specifically, I focus on intraday patterns of trading volume, market shares, quoted spreads, and 5-minute price impacts. Following Abhyankar et al. (1997) and Cai et al. (2004), I use 15-minute intraday averages and obtain 34 intervals across the trading day. 15-minute snapshots are small enough to capture intraday effects but at the same time level volatility of the trading process.

For trading volume, I multiply the traded quantity with the corresponding execution price and obtain the sum for each 15-minute interval per trading venue across stocks. Market shares are the fraction of total trading volume for each platform on a 15-minute basis. Quoted spreads and 5-minute price impacts are calculated as presented in Section 4.2 and averaged for each 15-minute interval and per stock.

To analyze intraday patterns of each variable, I rely on two methods. First, I graphically evaluate daily variations of each variable for both observation periods, Q1 and Q4. Second, to test for statistical significance of intraday changes, I use the following regression model similar to Cai et al. (2004):

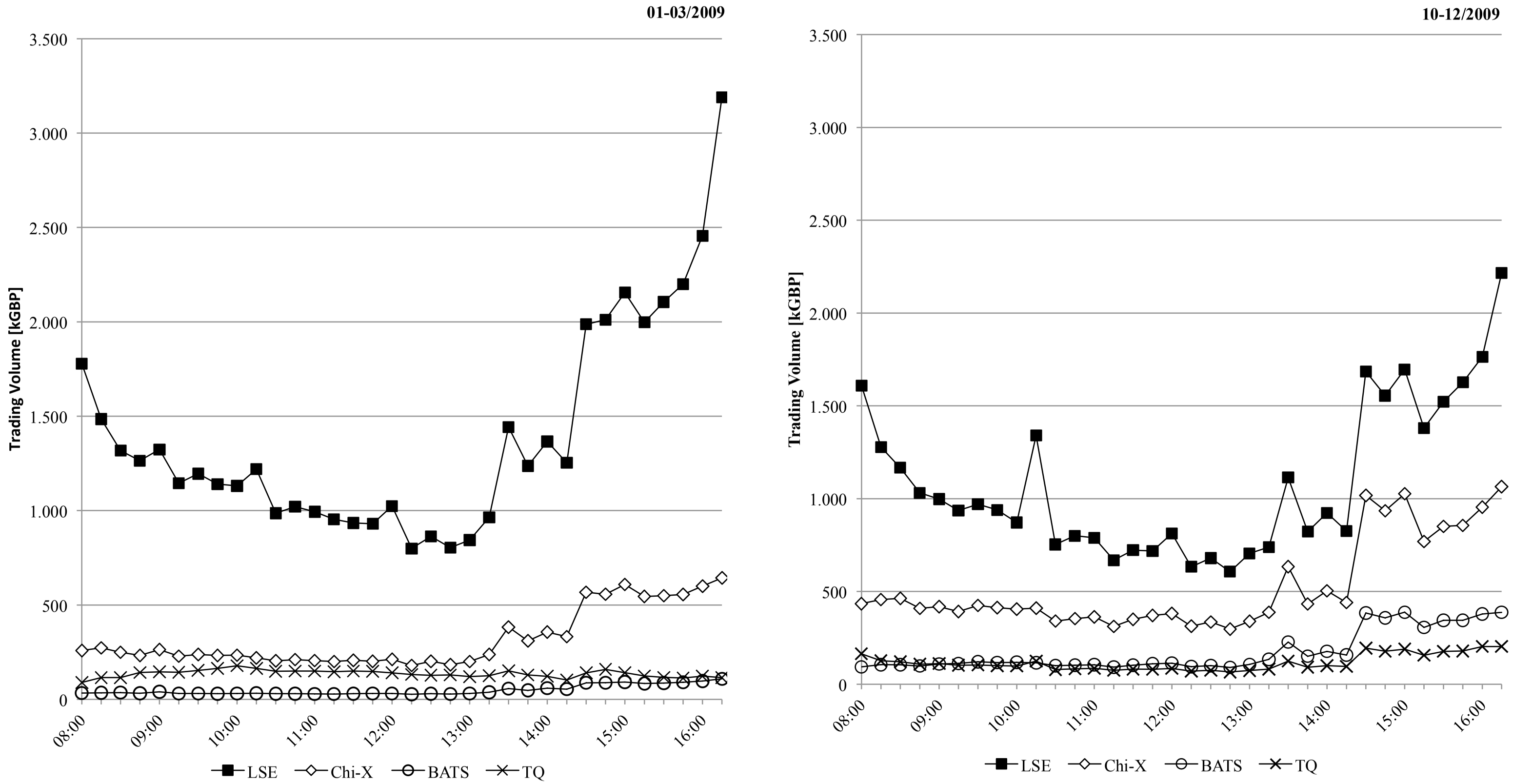
$$measure_{i,t} = \alpha_0 + \sum_{j=1}^{16} \beta_j D_{i,t,j} + \sum_{j=18}^{34} \beta_j D_{i,t,j} + \sum \gamma_j controls_{i,t} + \epsilon_{i,t} \tag{5.2}$$

where $measure_{i,t,j}$ represents my variables of interest, namely trading volume, market shares, quoted spreads, or 5-minute price impacts of stock i during the 15-minute interval j on trading day t. Dummy variables for each 15-minute interval of the trading day take the value 1 for an observation within this interval and 0 otherwise. I omit the midday interval, the 17th interval of the trading day from 12:00 to 12:15 which is my reference interval. Thus, all coefficients β_j measure the difference relative to this reference interval. I include firm and day dummy variables as controls and use robust clustered standard errors according to Thompson (2011) as in my previous regression model.

5.3.1 Trading Intensity

Trading Volume Figure 5.1 depicts average trading volume on the LSE, Chi-X, BATS and Turquoise for each 15-minute interval during Q1 and Q4 of 2009. For all intervals, the largest amount of volume is traded on the LSE. However, as stated in Section 5.2.2, it is also visible that trading volume shifts from the LSE towards the MTFs between Q1 and Q4, i.e. market fragmentation increases over time.

FIGURE 5.1: ***15-minute Snapshots of Intraday Trading Volumes on the LSE, Chi-X, BATS, and Turquoise.*** *The figure shows 15-minute intraday trading volume snapshots of 69 FTSE 100 constituents on the LSE, Chi-X, BATS, and Turquoise for Q1 and Q4 of 2009. I aggregate the trading volume for all executions on a 15-minute interval per day and per stock on each platform. Then, I obtain averages per platform over the two quarters.*



In Q1, Chi-X depicts the highest intraday trading volume among MTFs closely followed by Turquoise and BATS. The intraday patterns of the LSE and the three MTFs obviously differ. Trading volume on the LSE resembles a crude U-shaped pattern starting with average volumes of nearly 1,800,000 GBP per stock in the first 15-minutes of the trading day. Volume then decreases close to 800,000 GBP until 13:30 and rises to nearly 3,200,000 GBP in the last interval before market closing. This means that trading activity already peaks at market opening on the LSE. Compared to the LSE, trading volume on MTFs starts at lower levels ranging from 258,000 GBP (per stock) on Chi-X to 89,000 GBP on Turquoise down to 34,000 GBP on BATS during the first 15-minute interval. MTFs also show no distinct peak as the LSE does. In contrast to BATS and Turquoise, which depict continuously flat volume lines across the day, trading volume on Chi-X rises after 13:00 up to 643,000 GBP during the last intraday interval. I attribute the 13:00 co-movement in trading volume on the LSE and Chi-X to the US market opening.[10] The inter-connectivity of global markets may force investors to adopt their strategies to new information coming from the U.S. market.

In Q4, trading volume on Chi-X and BATS is generally higher compared to Q1 while trading on Turquoise is less active. The LSE still resembles a crude U-shape in trading volume while MTFs show no major volume changes from market opening until 13:00. All MTFs, particularly Chi-X, depict increasing trading volumes and an approaching co-movement to the LSE after 13:00. This result suggests that the market matures and grows closer together over time. My results depict for all venues, but particularly the LSE and Chi-X, a strong increase in trading volume within the last five intraday intervals in both quarters which may be connected to portfolio rebalancing activities before market closing.

Regression results in Table 5.3 confirm my graphically observed intraday patterns of trading volume. The reported coefficients show the difference of each 15-minute interval relative to the midday interval (*Intercept*) from 12:00 to 12:15.[11] I report robust

[10]US trading starts at 14:30 GMT, however, new market information is disseminated much earlier, often starting from 13:00 GMT.

[11]The regression coefficients slightly differ from the numbers in my figures, since the regression model controls for firm and time specific effects.

standard errors following Thompson (2011), t-statistics are presented in italic letters. "***" denotes significance at the 1% level, "**" at the 5% level, and "*" at the 10% level.

TABLE 5.3: ***Intraday regression results: Trading volume.*** *I compare 69 FTSE100 stocks traded on the LSE, Chi-X, BATS, and Turquoise between January 5 to March 31, 2009 (Q1) and October 1 to December 30, 2009 (Q4). I use the regression model presented in Equation 5.2. I report robust standard errors following Thompson (2011), t-statistics are presented in italic letters. '***' denotes significance at the 1% level, '**' at the 5% level, and '*' at the 10% level.*

	January to March 2009							
	LSE	t-stat.	Chi-X	t-stat.	BATS	t-stat.	TQ	t-stat.
Intercept	2,525.81	*35.84****	425.01	*25.10****	60.89	*67.30****	157.41	*7.45****
8:00	756.73	*3.91****	46.86	*2.66****	2.42	*0.84*	-50.72	*-5.97****
8:15	462.87	*4.20****	60.80	*3.07****	3.61	*1.26*	-24.51	*-2.95****
8:30	296.16	*3.89****	36.89	*2.27***	3.91	*1.31*	-25.34	*-3.71****
8:45	242.61	*3.56****	20.96	*1.53*	0.63	*0.32*	1.56	*0.27*
9:00	302.04	*4.54****	51.07	*3.45****	9.03	*2.92****	5.79	*1.03*
9:15	122.81	*2.50***	16.32	*1.45*	0.23	*0.12*	3.17	*0.56*
9:30	173.29	*3.20****	25.55	*2.20***	0.19	*0.09*	13.03	*1.98***
9:45	119.08	*2.19***	20.89	*1.83**	-0.62	*-0.35*	23.65	*3.42****
10:00	109.12	*1.89**	21.87	*1.78**	-0.28	*-0.13*	38.02	*4.01****
10:15	197.94	*1.41*	8.39	*0.72*	0.74	*0.30*	23.94	*3.06****
10:30	-35.37	*-0.79*	-8.35	*-0.94*	-1.53	*-0.77*	9.07	*1.69**
10:45	-1.61	*-0.02*	-1.87	*-0.13*	-0.73	*-0.25*	9.95	*1.46*
11:00	-28.97	*-0.59*	-7.23	*-0.67*	-2.69	*-1.46*	9.41	*1.40*
11:15	-68.77	*-1.45*	-11.41	*-1.11*	-2.73	*-1.57*	6.06	*1.07*
11:30	-88.61	*-1.74**	-4.98	*-0.47*	-1.50	*-0.88*	10.05	*1.59*
11:45	-92.61	*-2.55***	-10.06	*-1.50*	-0.44	*-0.30*	7.53	*1.61*
12:15	-224.72	*-4.26****	-33.69	*-3.94****	-4.50	*-3.33****	-9.10	*-1.93***
12:30	-162.69	*-2.91****	-11.18	*-1.13*	-0.78	*-0.41*	-13.83	*-2.77****
12:45	-222.82	*-3.64****	-29.23	*-3.46****	-3.55	*-2.07***	-11.71	*-2.27***
13:00	-183.66	*-3.27****	-12.25	*-1.54*	0.14	*0.06*	-20.38	*-3.68****
13:15	-62.99	*-1.17*	24.11	*2.02***	6.17	*3.07****	-15.08	*-2.32***
13:30	414.52	*4.28****	169.29	*4.63****	25.35	*4.99****	9.73	*1.32*
13:45	206.61	*2.78****	95.87	*3.72****	15.78	*4.24****	-11.11	*-1.54*
14:00	335.18	*3.80****	141.72	*4.36****	27.43	*4.88****	-19.62	*-2.63****
14:15	220.64	*3.43****	117.93	*4.51****	22.43	*6.01****	-38.21	*-4.47****
14:30	951.36	*6.10****	351.77	*5.67****	55.86	*7.40****	-1.16	*-0.16*
14:45	974.95	*6.93****	341.29	*6.43****	56.64	*7.56****	17.38	*2.37***
15:00	1,117.31	*6.77****	392.62	*6.38****	59.63	*7.25****	-0.62	*-0.09*
15:15	956.12	*7.31****	327.71	*6.70****	52.30	*7.40****	-18.28	*-2.17***
15:30	1,059.27	*7.36****	330.98	*6.94****	54.48	*7.20****	-26.49	*-3.00****
15:45	1,143.36	*7.70****	334.33	*7.30****	57.72	*7.41****	-30.60	*-3.57****
16:00	1,385.05	*7.90****	374.32	*7.33****	63.68	*7.69****	-22.32	*-2.38***
16:15	2,090.52	*8.83****	409.74	*7.56****	74.75	*8.05****	-33.32	*-3.60****
Obs.	141,671		141,671		141,671		141,671	
R^2	48.37%		55.97%		36.79%		52.10%	

continued on the next page. . .

. . . continued from Table 5.3

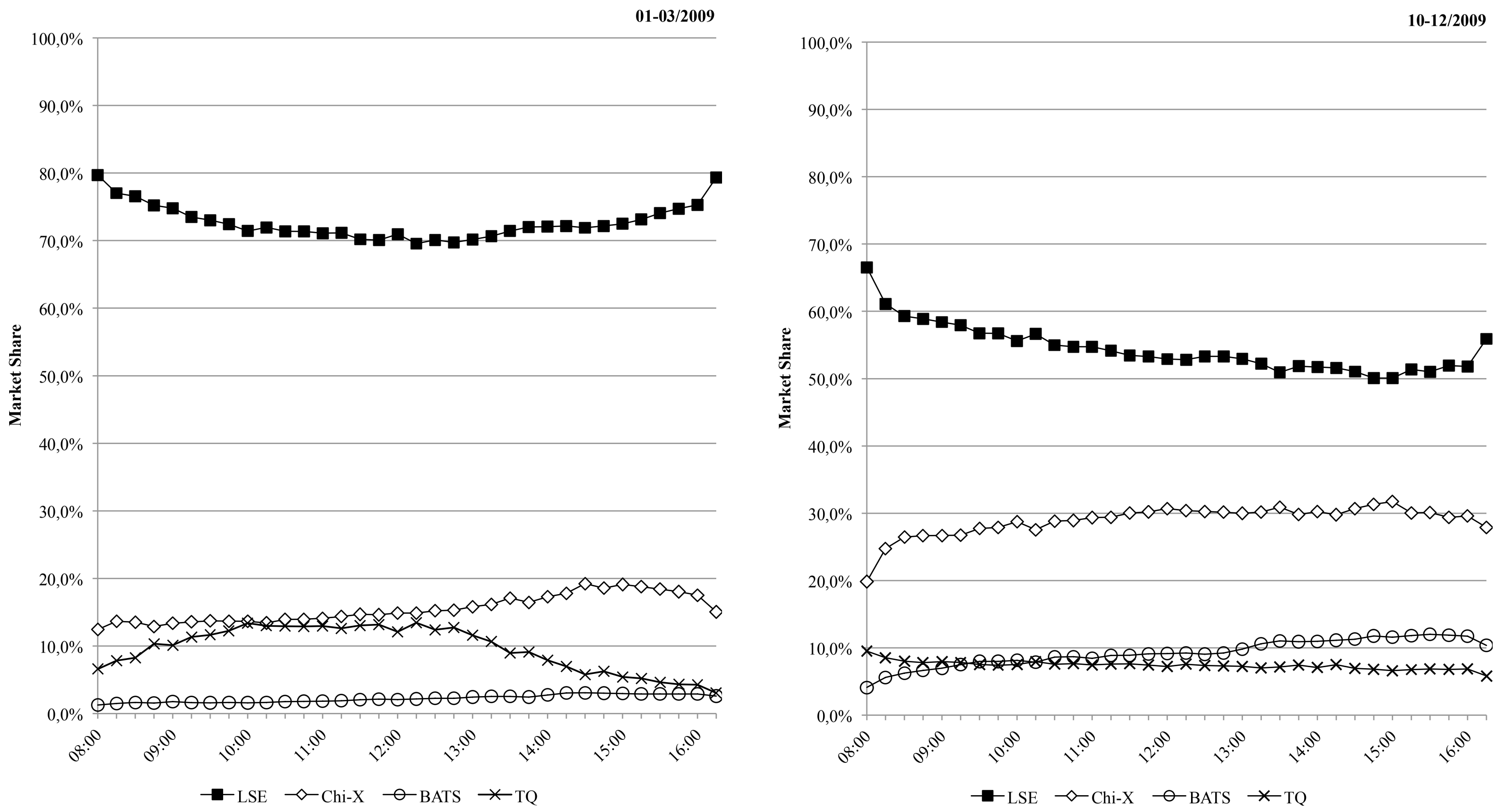
	October to December 2009							
	LSE	t-stat.	Chi-X	t-stat.	BATS	t-stat.	TQ	t-stat.
Intercept	1,909.26	*18.91****	1022.79	*21.43****	270.82	*14.96****	76.64	*8.30****
8:00	796.55	*4.89****	53.12	*1.49*	-20.53	*-2.19***	79.02	*5.70****
8:15	465.41	*3.83****	74.97	*2.04***	-7.88	*-0.80*	40.93	*3.70****
8:30	353.92	*3.55****	81.51	*2.39***	-9.53	*-1.11*	35.26	*3.68****
8:45	218.41	*2.86****	28.16	*1.05*	-15.24	*-2.02***	23.09	*2.95****
9:00	184.84	*2.63****	36.44	*1.36*	-5.12	*-0.61*	25.97	*3.63****
9:15	122.97	*1.90**	10.42	*0.39*	-1.66	*-0.19*	16.93	*2.48***
9:30	157.22	*2.41***	43.79	*1.53*	6.72	*0.84*	18.55	*2.60****
9:45	126.86	*1.98***	31.66	*1.25*	3.39	*0.43*	14.67	*2.28***
10:00	59.42	*0.99*	23.72	*0.94*	3.65	*0.50*	12.28	*1.86**
10:15	527.12	*1.87**	29.79	*1.32*	2.11	*0.30*	38.89	*1.32*
10:30	-58.91	*-1.10*	-41.09	*-1.94**	-14.04	*-2.05***	-6.34	*-1.34*
10:45	-12.71	*-0.18*	-27.99	*-1.23*	-11.10	*-1.62*	-2.42	*-0.55*
11:00	-23.27	*-0.45*	-17.91	*-0.79*	-9.24	*-1.38*	0.42	*0.08*
11:15	-144.05	*-2.59****	-68.93	*-3.07****	-21.15	*-3.04****	-10.05	*-1.97***
11:30	-89.77	*-1.79**	-31.25	*-1.41*	-11.48	*-1.87**	-3.92	*-0.77*
11:45	-94.17	*-2.07***	-9.88	*-0.46*	-3.38	*-0.58*	-5.17	*-1.25*
12:15	-179.56	*-3.74****	-68.52	*-3.59****	-18.67	*-3.10****	-15.03	*-3.40****
12:30	-133.02	*-2.16****	-44.74	*-1.58*	-13.56	*-1.54*	-10.61	*-1.67**
12:45	-206.09	*-3.52****	-83.07	*-3.45****	-23.97	*-3.31****	-18.74	*-3.54****
13:00	-107.08	*-1.77**	-41.57	*-1.79**	-6.49	*-0.88*	-11.71	*-2.18***
13:15	-74.17	*-1.18*	6.11	*0.24*	20.53	*2.58****	-3.89	*-0.68*
13:30	301.37	*2.35***	252.75	*3.68****	113.01	*4.37****	38.80	*3.12****
13:45	10.06	*0.13*	51.27	*1.32*	36.33	*2.59****	5.97	*0.83*
14:00	110.82	*1.31*	121.90	*2.60****	63.52	*3.74****	14.47	*1.75**
14:15	12.60	*0.18*	58.67	*1.82**	43.87	*3.82****	11.07	*1.62*
14:30	872.23	*6.40****	635.61	*6.39****	269.62	*6.57****	109.64	*7.86****
14:45	741.65	*5.87****	553.04	*6.23****	243.93	*6.50****	92.71	*6.90****
15:00	884.10	*6.06****	644.68	*6.36****	274.08	*6.48****	104.03	*6.85****
15:15	567.08	*5.87****	387.52	*6.48****	192.10	*7.13****	71.00	*6.89****
15:30	708.68	*5.98****	467.72	*6.42****	229.82	*6.90****	91.76	*7.20****
15:45	812.66	*6.17****	472.81	*6.54****	229.77	*7.04****	92.87	*7.44****
16:00	947.53	*7.32****	568.72	*7.14****	262.93	*7.48****	117.47	*7.77****
16:15	1,377.17	*8.36****	668.49	*8.11****	268.69	*8.81****	115.30	*7.48****
Obs.	142,534		142,534		142,534		142,534	
R^2	36.55%		50.82%		44.42%		36.29%	

For the LSE, my findings of a crude U-shape in trading volume are consistent with the theoretical predictions of Brock and Kleidon (1992) who argue that trading volume is concentrated at market opening and closing. Investors react on new information at the beginning of a trading day and adapt their holdings for an overnight position before market closing. Similar to Abhyankar et al. (1997) and Cai et al. (2004), I find an increase in trading volume before U.S. market opening on the LSE and Chi-X in Q1 and on all venues in Q4. In addition, my findings confirm an increase in trading volume on the LSE and Chi-X in Q1 and on all platforms in Q4 during the last trading hour of a trading day, potentially due to portfolio rebalancing for the overnight period. Intraday trading volume also shows that Chi-X is the only MTF that follows a similar pattern as the LSE, at least during the second part of the trading day.

Market Shares Figure 5.2 depicts intraday patterns of market shares for all four trading venues. The LSE is the largest trading venue with highest traded volumes over both quarters. However, the figure also displays a shift in market shares away from the LSE towards the MTFs from Q1 to Q4.

In Q1, the LSE dominates Chi-X, BATS, and Turquoise as the most active platform throughout the trading day. LSE's market share follows a clear U-shape during the trading day with a peak at around 80.0% at market opening and closing. During the trading day, LSE's share in trading volume drops by about 10.0 percentage points. In contrast to the LSE, Chi-X and Turquoise depict an inverted U-shape with Turquoise gaining more market share at the beginning and Chi-X at the end of the trading day.

FIGURE 5.2: ***15-minute Snapshots of Intraday Market Shares on the LSE, Chi-X, BATS, and Turquoise.*** *The figure shows 15-minute intraday market share snapshots of 69 FTSE 100 constituents on the LSE Chi-X, BATS, and Turquoise for Q1 and Q4 of 2009. I aggregate the trading volume for all executions on a 15-minute interval per day and per stock on each platform. Market shares represent each platform's fraction of trading volume for every 15-minute interval. Then I obtain averages per platform over the two quarters.*



In Q4, the LSE again exhibits an U-shape, however with a slighter increase in trading activity during the second half of the trading day. Chi-X still leads the MTFs as most active trading platform in Q4. Intraday market shares increase on both MTFs, Chi-X and BATS, until 15:00. Afterwards, trading activity slowly shifts back to the LSE. Particularly during the last 15 minutes of the trading day, I observe a strong increase of 4.0 percentage points in Q1 on the LSE relative to the three MTFs, and 4.1 percentage points in Q4. In Q4, Turquoise does not resemble an inverted U-shape anymore but loses market shares from an initial high at the beginning of the trading day until the end.

My regression results in Table 5.4 confirm my graphical findings for both quarters. The shifts in intraday trading activity between the regulated market and MTFs may indicate that investors put more trust in the price formation process of the LSE during market opening and closing. Foster and Viswanathan (1993) emphasize a positive relationship between higher volatility, i.e., price uncertainty, at the market opening and closing and an increased adverse selection risk. Intuitively, investors prefer the most liquid and stable market under such circumstances, especially when they have an increased desire to trade in these periods due to portfolio rebalancing (Brock and Kleidon (1992)). Investors even seem to be willing to accept the price premium at the LSE during such market conditions since explicit transaction costs on MTFs are lower (compare Section 2.2). Thus, my findings accentuate the importance of traditional exchanges in the price formation process in an increasingly fragmented European market environment.

TABLE 5.4: ***Intraday regression results: Market shares.*** *I compare 69 FTSE100 stocks traded on the LSE, Chi-X, BATS, and Turquoise between January 5 to March 31, 2009 (1st quarter) and October 1 to December 30, 2009 (4th quarter). I use the regression model presented in equation 5.2 I report robust standard errors following Thompson (2011), t-statistics are presented in italic letters. '***' denotes significance at the 1% level, '**' at the 5% level, and '*' at the 10% level.*

	January to March 2009							
	LSE	t-stat.	Chi-X	t-stat.	BATS	t-stat.	TQ	t-stat.
Intercept	74.00%	*156.36****	17.37%	*82.45****	2.47%	*35.24****	6.16%	*51.25****
8:00	8.76%	*11.69****	-2.43%	*-5.20****	-0.82%	*-7.42****	-5.50%	*-10.23****
8:15	6.08%	*9.20****	-1.22%	*-2.97****	-0.60%	*-5.50****	-4.26%	*-8.52****
8:30	5.61%	*9.62****	-1.33%	*-3.27****	-0.44%	*-4.46****	-3.84%	*-8.85****
8:45	4.27%	*7.61****	-1.97%	*-5.22****	-0.53%	*-5.87****	-1.78%	*-4.95****
9:00	3.85%	*6.20****	-1.53%	*-3.89****	-0.33%	*-3.51****	-1.99%	*-6.02****
9:15	2.54%	*4.92****	-1.31%	*-3.76****	-0.46%	*-4.75****	-0.77%	*-2.61****
9:30	2.09%	*3.96****	-1.15%	*-3.44****	-0.49%	*-6.00****	-0.45%	*-1.40*
9:45	1.46%	*3.18****	-1.18%	*-4.11****	-0.44%	*-4.97****	0.16%	*0.53*
10:00	0.45%	*0.80*	-1.21%	*-3.97****	-0.51%	*-4.87****	1.27%	*3.84****
10:15	1.01%	*1.71**	-1.46%	*-3.63****	-0.44%	*-4.38****	0.89%	*3.10****
10:30	0.44%	*0.92*	-0.94%	*-3.22****	-0.31%	*-3.22****	0.82%	*2.73****
10:45	0.40%	*0.88*	-0.92%	*-3.01****	-0.28%	*-3.12****	0.79%	*2.84****
11:00	0.17%	*0.33*	-0.77%	*-2.66****	-0.26%	*-3.07****	0.86%	*2.78****
11:15	0.18%	*0.38*	-0.53%	*-1.86**	-0.19%	*-2.16***	0.54%	*2.07***
11:30	-0.74%	*-1.75**	-0.17%	*-0.69*	-0.04%	*-0.64*	0.96%	*3.54****
11:45	-0.88%	*-2.29***	-0.25%	*-1.25*	0.06%	*0.85*	1.07%	*4.50****
12:15	-1.41%	*-3.81****	-0.01%	*-0.03*	0.06%	*0.96*	1.35%	*5.81****
12:30	-0.83%	*-1.98***	0.34%	*1.23*	0.16%	*2.65****	0.33%	*1.37*
12:45	-1.22%	*-3.18****	0.40%	*1.65**	0.16%	*1.90**	0.65%	*2.57***
13:00	-0.77%	*-1.84**	0.91%	*3.55****	0.34%	*3.76****	-0.49%	*-2.00***
13:15	-0.29%	*-0.66*	1.27%	*4.14****	0.45%	*5.17****	-1.44%	*-5.35****
13:30	0.47%	*0.99*	2.19%	*6.74****	0.44%	*4.63****	-3.10%	*-9.01****
13:45	1.08%	*2.38***	1.55%	*4.91****	0.35%	*4.46****	-2.97%	*-8.59****
14:00	1.13%	*2.37***	2.38%	*7.00****	0.66%	*7.20****	-4.17%	*-10.94****
14:15	1.25%	*2.41***	2.88%	*9.26****	0.97%	*8.94****	-5.10%	*-10.77****
14:30	0.99%	*1.66**	4.30%	*12.00****	1.00%	*8.56****	-6.29%	*-11.86****
14:45	1.27%	*2.28***	3.65%	*10.96****	0.93%	*8.16****	-5.84%	*-11.51****
15:00	1.60%	*2.65****	4.19%	*10.96****	0.88%	*7.50****	-6.68%	*-12.11****
15:15	2.26%	*3.83****	3.83%	*9.68****	0.82%	*6.83****	-6.90%	*-12.19****
15:30	3.22%	*4.88****	3.47%	*8.42****	0.80%	*6.69****	-7.49%	*-12.33****
15:45	3.93%	*5.62****	3.05%	*8.05****	0.81%	*6.21****	-7.80%	*-12.16****
16:00	4.55%	*6.35****	2.51%	*6.15****	0.81%	*6.20****	-7.87%	*-12.52****
16:15	8.71%	*12.33****	-0.01%	*-0.02*	0.49%	*4.29****	-9.19%	*-13.98****
Obs.	141,668		141,668		141,668		141,668	
R^2	22.15%		28.30%		13.94%		36.76%	

continued on the next page...

. . . continued from Table 5.4

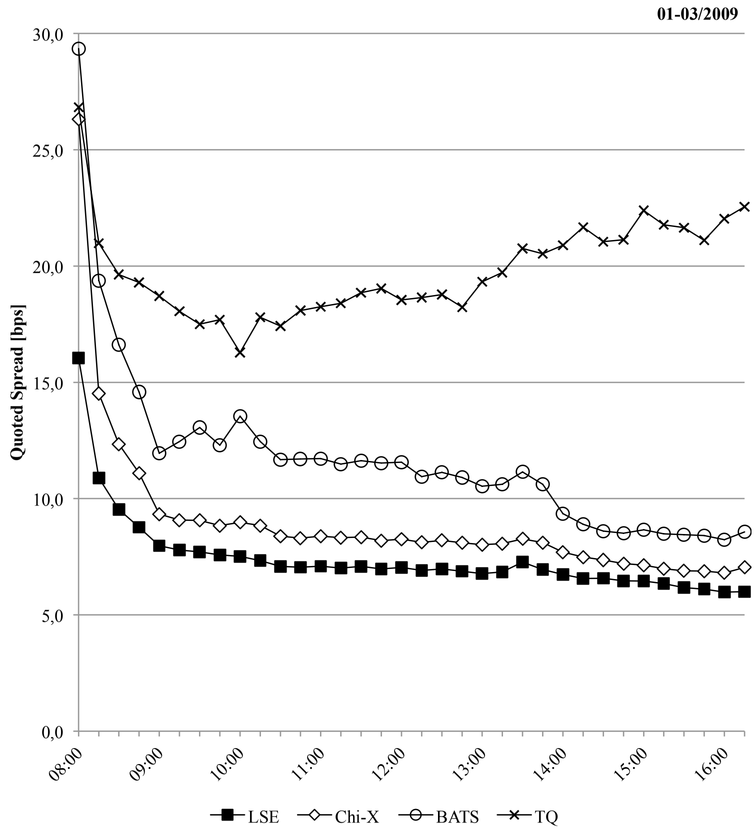
				October to December 2009				
	LSE	t-stat.	Chi-X	t-stat.	BATS	t-stat.	TQ	t-stat.
Intercept	56.34%	*79.17****	32.84%	*67.97****	8.47%	*45.68****	2.35%	*22.30****
8:00	13.62%	*14.15****	-10.88%	*-16.16****	-5.01%	*-12.70****	2.28%	*5.58****
8:15	8.21%	*8.93****	-5.98%	*-8.73****	-3.53%	*-9.44****	1.29%	*3.28****
8:30	6.36%	*7.38****	-4.24%	*-7.13****	-2.90%	*-8.89****	0.78%	*2.48***
8:45	5.97%	*7.15****	-4.06%	*-6.84****	-2.49%	*-8.25****	0.58%	*2.21***
9:00	5.49%	*6.72****	-4.03%	*-7.26****	-2.17%	*-8.03****	0.71%	*2.76****
9:15	5.04%	*6.55****	-3.99%	*-8.03****	-1.64%	*-5.90****	0.59%	*2.59****
9:30	3.84%	*4.82****	-2.97%	*-5.76****	-1.14%	*-4.04****	0.28%	*1.12*
9:45	3.82%	*4.87****	-2.83%	*-5.62****	-1.15%	*-4.28****	0.16%	*0.71*
10:00	2.68%	*3.71****	-1.98%	*-4.39****	-0.99%	*-3.75****	0.30%	*1.47*
10:15	3.71%	*3.70****	-3.15%	*-5.80****	-1.28%	*-4.87****	0.72%	*0.95*
10:30	2.08%	*4.37****	-1.89%	*-5.28****	-0.53%	*-2.72****	0.33%	*1.76**
10:45	1.82%	*3.47****	-1.79%	*-5.00****	-0.45%	*-2.68****	0.42%	*2.21***
11:00	1.83%	*4.18****	-1.37%	*-4.53****	-0.70%	*-4.23****	0.24%	*1.41*
11:15	1.22%	*2.80****	-1.30%	*-3.42****	-0.29%	*-1.78**	0.36%	*2.69****
11:30	0.55%	*1.30*	-0.69%	*-2.15***	-0.25%	*-1.54*	0.39%	*2.27***
11:45	0.33%	*0.90*	-0.51%	*-1.73**	-0.03%	*-0.25*	0.20%	*1.47*
12:15	-0.11%	*-0.24*	-0.31%	*-0.98*	0.11%	*0.59*	0.31%	*1.83**
12:30	0.38%	*0.74*	-0.43%	*-1.39*	-0.09%	*-0.38*	0.14%	*0.78*
12:45	0.39%	*0.57*	-0.58%	*-1.40*	0.11%	*0.46*	0.08%	*0.44*
13:00	0.03%	*0.03*	-0.72%	*-1.41*	0.68%	*2.28***	0.02%	*0.10*
13:15	-0.69%	*-0.65*	-0.53%	*-0.78*	1.46%	*4.94****	-0.24%	*-1.01*
13:30	-1.99%	*-1.78**	0.19%	*0.27*	1.88%	*5.50****	-0.08%	*-0.38*
13:45	-1.06%	*-0.93*	-0.90%	*-1.22*	1.76%	*4.89****	0.21%	*0.86*
14:00	-1.19%	*-1.32*	-0.46%	*-0.76*	1.83%	*6.11****	-0.17%	*-0.84*
14:15	-1.30%	*-1.40*	-0.95%	*-1.55*	1.98%	*5.97****	0.27%	*1.24*
14:30	-1.86%	*-2.02***	-0.01%	*-0.01*	2.15%	*6.61****	-0.28%	*-1.23*
14:45	-2.87%	*-3.38****	0.63%	*1.14*	2.64%	*8.28****	-0.40%	*-2.02***
15:00	-2.88%	*-3.49****	1.05%	*1.92**	2.45%	*7.84****	-0.62%	*-3.31****
15:15	-1.64%	*-1.93**	-0.62%	*-1.09*	2.69%	*8.36****	-0.43%	*-2.05***
15:30	-1.99%	*-2.55***	-0.56%	*-1.03*	2.88%	*8.90****	-0.34%	*-1.72**
15:45	-1.12%	*-1.32*	-1.27%	*-2.28***	2.79%	*8.49****	-0.40%	*-1.90**
16:00	-1.26%	*-1.77**	-1.04%	*-2.11***	2.65%	*8.82****	-0.34%	*-1.61*
16:15	2.75%	*3.47****	-2.73%	*-4.82****	1.34%	*4.07****	-1.36%	*-5.33****
Obs.	142,480		142,480		142,480		142,480	
R^2	15.89%		12.94%		24.10%		12.42%	

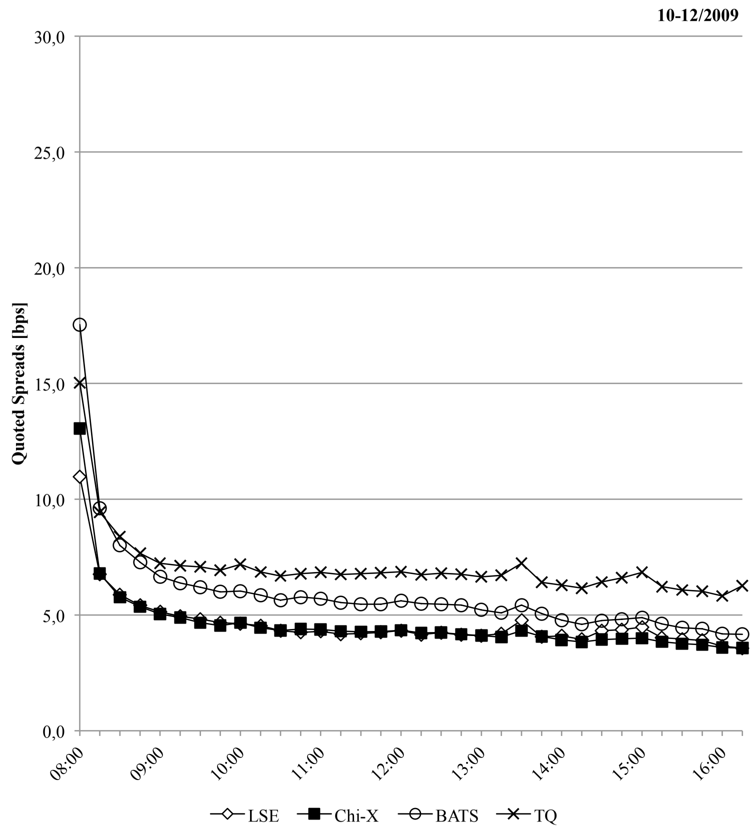
5.3.2 Liquidity

Figure 5.3 reports intraday patterns of quoted spreads for all four trading venues. In line with my interday analysis, I find that quoted spreads decrease for every 15-minute interval on each platform from Q1 to Q4. I observe that quoted spreads on MTFs approach the LSE level and show a stronger co-movement with the regulated market over time.

In Q1, the LSE shows the smallest quoted spreads for each 15-minute interval compared to the other platforms. Spreads on Chi-X follow very closely the liquidity patterns on the LSE. BATS and Turquoise exhibit larger and more volatile spreads over the trading day. On all platforms, spreads are relatively large at market opening and narrow quickly during the first 75 minutes of the trading day. During this period, spreads on the LSE drop by -52.5%, on Chi-X by -65.6%, on BATS by -57.6%, and on Turquoise by -32.7% compared to the first 15-minute interval. In the last half hour of the trading day, quoted spreads increase on all venues. This increase is stronger on MTFs with 3.5% on Chi-X, 4.0% on BATS, and 2,3% on Turquoise, compared to 0.2% on the LSE. On the LSE, Chi-X and BATS quoted spreads thus follow a (crude) reversed J-shaped pattern. Spreads on Turquoise exhibit a differing pattern, which resembles a crude U-shape. They narrow after market opening until 10:00 but then start a slight but steady increase until market closing.

FIGURE 5.3: ***15-minute Snapshots of Intraday Quoted Spreads on the LSE, Chi-X, BATS, and Turquoise.*** *The figure shows average intraday 15-minute quoted spread snapshots of 69 FTSE 100 constituents on the LSE Chi-X, BATS, and Turquoise for Q1 and Q4 of 2009. I calculate average quoted spreads as presented in Section 4.2.2. I aggregate the trading volume for all executions on a 15-minute interval per day and per stock on each platform. Market shares represent each platform's fraction of trading volume for very 15-minute interval. Then I obtain averages per platform over the two quarters.*





In Q4, quoted spreads on all trading venues are of similar magnitude and exhibit a strong co-movement over the day. Again, liquidity decreases quickly during the first 75 minutes of the trading day. Afterwards, spreads slowly narrow during the remaining trading day, again resembling a reversed J-shape. There is an exception at 13:30 were spreads on all venues widen for one 15-minute interval.[12] I attribute this spread increase to higher uncertainty due to new information arrival from the U.S. market opening. Compared to Q1, spreads on the LSE, Chi-X, and BATS do not widen shortly before market closing. Turquoise is the only platform, which exhibits increasing spreads in the last 30 minutes of the trading day in Q4. My regression results support my graphical findings, with the exception of the 13:30 spread increase. Regression results only document a highly significant increase on the LSE during this period.

The (crude) reversed J-shaped pattern of quoted spreads which I find on the LSE, Chi-X, BATS, and Turquoise in Q4 is also documented by McInish and Wood (1992), Abhyankar et al. (1997), and Cai et al. (2004). The crude U-shape on Turquoise and the slight spread increases at the end of the trading day on the LSE, Chi-X, and BATS in Q1 are in line with theoretical predictions of Brock and Kleidon (1992). Looking at the relationship between trading volume and quoted spreads, my findings document a negative correlation on all MTFs. This indicates that liquidity on MTFs increases over the day along with decreasing spreads. McInish and Wood (1992), Kleidon and Werner (1993), and Cai et al. (2004) also document this intuitively expected relationship. On the LSE, I do not find this inverse relationship within the trading day. In contrast to the MTFs, trading volume on the LSE is high while quoted spreads are wide during the first hour of the trading day. This finding again indicates the important function of the regulated market in a fragmented European market environment. Investors seem to accept higher implicit transaction costs on the LSE relative to MTFs in order to profit from price discovery on the traditional exchange during market opening.

[12]In Q1, I find a similar increase in quoted spreads on the LSE, Chi-X, and BATS.

TABLE 5.5: ***Intraday regression results: Quoted spreads.*** *I compare 69 FTSE100 stocks traded on the LSE, Chi-X, BATS, and Turquoise between January 5 to March 31, 2009 (1st quarter) and October 1 to December 30, 2009 (4th quarter). I use the regression model presented in equation 5.2 I report robust standard errors following Thompson (2011), t-statistics are presented in italic letters. '***' denotes significance at the 1% level, '**' at the 5% level, and '*' at the 10% level.*

	January to March 2009							
	LSE	t-stat.	Chi-X	t-stat.	BATS	t-stat.	TQ	t-stat.
Intercept	6.096	*63.94******	6.253	*51.31******	10.700	*43.61******	19.375	*46.72******
8:00	8.997	*11.55******	18.044	*11.99******	17.778	*11.72******	8.276	*2.23****
8:15	3.845	*9.91******	6.251	*9.49******	7.796	*8.56******	2.429	*0.71*
8:30	2.491	*8.86******	4.082	*8.98******	5.037	*7.43******	1.080	*0.35*
8:45	1.725	*8.27******	2.838	*8.57******	3.005	*5.94******	0.744	*0.41*
9:00	0.922	*6.78******	1.069	*5.90******	0.371	*0.82*	0.160	*0.11*
9:15	0.745	*6.71******	0.811	*5.20******	0.879	*1.84**	-0.499	*-0.38*
9:30	0.664	*6.18******	0.795	*4.92******	1.484	*3.06******	-1.051	*-0.64*
9:45	0.533	*5.66******	0.572	*4.59******	0.722	*1.53*	-0.862	*-0.60*
10:00	0.467	*5.37******	0.711	*4.79******	1.963	*3.66******	-2.270	*-0.95*
10:15	0.288	*3.42******	0.581	*3.76******	0.875	*2.06****	-0.756	*-0.86*
10:30	0.038	*0.56*	0.115	*1.15*	0.103	*0.25*	-1.133	*-1.15*
10:45	0.007	*0.11*	0.039	*0.44*	0.131	*0.30*	-0.446	*-1.18*
11:00	0.046	*0.80*	0.125	*1.61*	0.155	*0.72*	-0.288	*-0.68*
11:15	-0.030	*-0.52*	0.063	*0.89*	-0.087	*-0.42*	-0.143	*0.54*
11:30	0.044	*0.61*	0.091	*1.12*	0.058	*0.41*	0.310	*1.24*
11:45	-0.066	*-1.43*	-0.063	*-1.32*	-0.038	*-0.21*	0.497	*0.75*
12:15	-0.132	*-3.71******	-0.126	*-3.25******	-0.618	*-1.67**	0.096	*0.27*
12:30	-0.064	*-1.13*	-0.045	*-0.63*	-0.425	*-1.17*	0.215	*0.32*
12:45	-0.161	*-2.92******	-0.142	*-2.26****	-0.642	*-1.71**	-0.327	*-0.96*
13:00	-0.255	*-4.52******	-0.214	*-2.96******	-1.020	*-3.01******	0.745	*1.39*
13:15	-0.183	*-2.62******	-0.165	*-1.43*	-0.927	*-2.39****	1.154	*0.62*
13:30	0.240	*2.30****	0.037	*0.27*	-0.395	*-1.07*	2.172	*3.39******
13:45	-0.084	*-1.04*	-0.118	*-0.97*	-0.922	*-2.40****	1.937	*3.28******
14:00	-0.286	*-3.17******	-0.517	*-4.39******	-2.179	*-4.07******	2.334	*4.85******
14:15	-0.458	*-5.67******	-0.724	*-5.26******	-2.634	*-4.45******	3.166	*3.45******
14:30	-0.440	*-4.76******	-0.841	*-5.33******	-2.907	*-4.62******	2.720	*3.67******
14:45	-0.551	*-5.73******	-0.995	*-5.68******	-2.996	*-5.07******	2.878	*3.51******
15:00	-0.549	*-5.54******	-1.050	*-5.94******	-2.835	*-5.27******	4.189	*2.94******
15:15	-0.655	*-6.42******	-1.192	*-7.60******	-2.992	*-4.73******	3.612	*3.42******
15:30	-0.812	*-7.86******	-1.250	*-8.09******	-2.994	*-5.02******	3.563	*4.21******
15:45	-0.850	*-8.40******	-1.233	*-8.07******	-2.988	*-4.87******	3.244	*4.41******
16:00	-0.942	*-8.95******	-1.260	*-8.00******	-3.095	*-4.82******	4.384	*3.34******
16:15	-0.842	*-9.36******	-0.910	*-6.41******	-2.642	*-4.36******	5.603	*7.09******
Obs.	141,671		141,671		141,671		141,671	
R^2	71.07%		53.81%		16.93%		13.55%	

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... continued from Table 5.5

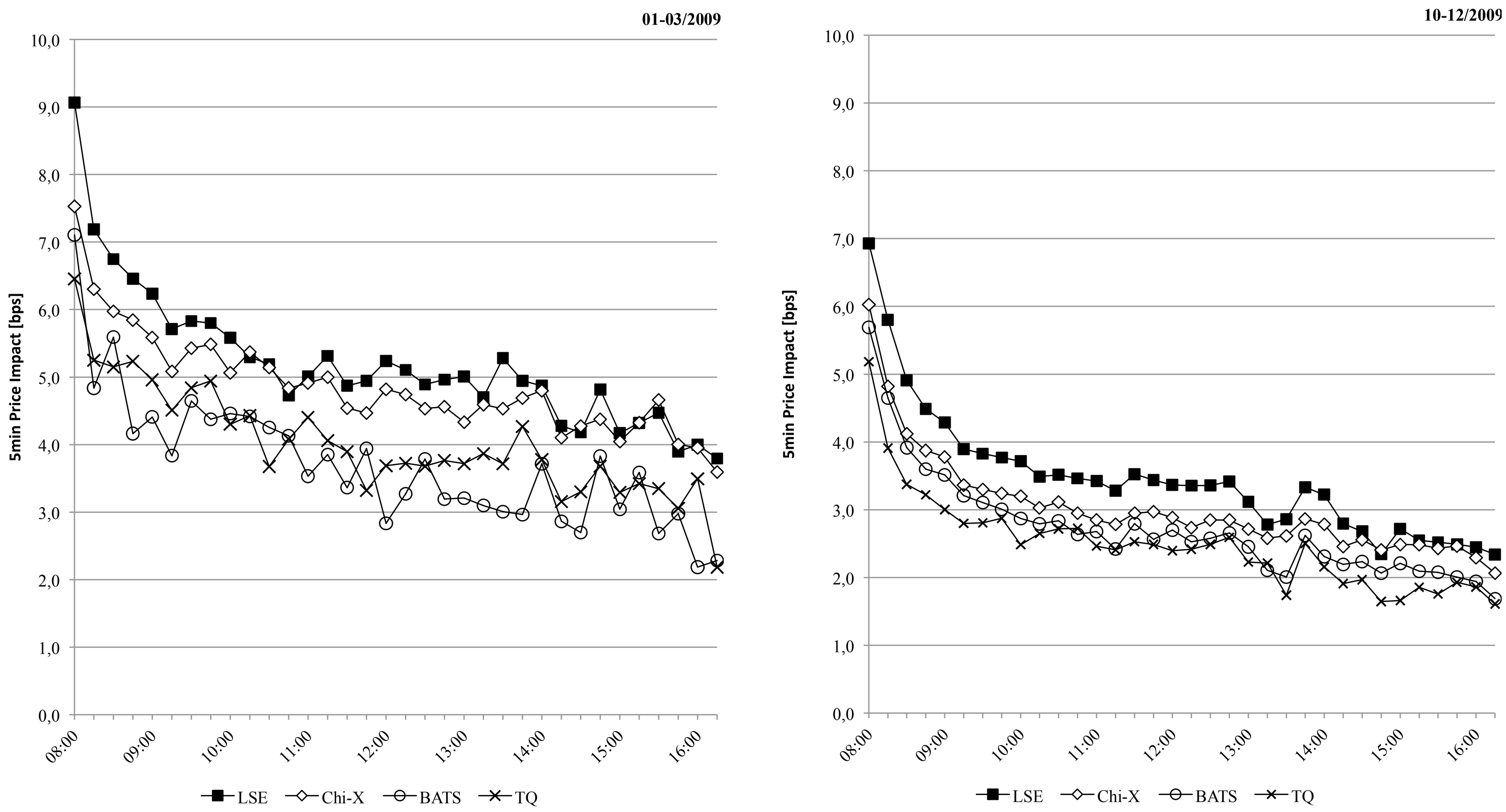
	October to December 2009							
	LSE	t-stat.	Chi-X	t-stat.	BATS	t-stat.	TQ	t-stat.
Intercept	5.317	*84.59****	5.486	*78.11****	6.619	*23.34****	10.646	*20.08****
8:00	6.657	*16.85****	8.720	*16.13****	11.926	*15.57****	8.157	*13.67****
8:15	2.428	*13.72****	2.456	*9.55****	4.003	*8.43****	2.573	*6.67****
8:30	1.553	*11.82****	1.431	*6.87****	2.388	*6.13****	1.515	*4.27****
8:45	1.080	*10.17****	1.020	*5.22****	1.670	*4.36****	0.796	*2.33***
9:00	0.805	*8.45****	0.709	*3.87****	1.048	*2.91****	0.367	*1.11*
9:15	0.619	*6.62****	0.554	*3.14****	0.769	*2.20***	0.261	*0.79*
9:30	0.496	*5.80****	0.336	*2.00***	0.584	*1.71**	0.205	*0.64*
9:45	0.338	*4.17****	0.210	*1.27*	0.385	*1.16*	0.067	*0.20*
10:00	0.297	*3.03****	0.334	*1.81**	0.421	*1.26*	0.322	*0.90*
10:15	0.209	*2.54***	0.116	*0.70*	0.244	*0.73*	-0.013	*-0.04*
10:30	-0.007	*-0.11*	-0.005	*-0.04*	0.027	*0.10*	-0.181	*-0.73*
10:45	-0.078	*-1.53*	0.055	*1.77**	0.167	*2.24***	-0.086	*-0.92*
11:00	-0.033	*-0.70*	0.045	*1.13*	0.089	*1.20*	-0.028	*-0.42*
11:15	-0.157	*-3.00****	-0.033	*-1.16*	-0.069	*-0.78*	-0.117	*-1.66**
11:30	-0.131	*-2.99****	-0.063	*-2.32***	-0.150	*-1.41*	-0.088	*-1.64*
11:45	-0.084	*-2.74****	-0.047	*-2.19***	-0.147	*-1.60*	-0.047	*-1.06*
12:15	-0.168	*-4.20****	-0.109	*-5.27****	-0.116	*-3.35****	-0.134	*-3.07****
12:30	-0.086	*-1.52*	-0.094	*-2.66****	-0.146	*-2.78****	-0.067	*-1.12*
12:45	-0.190	*-4.20****	-0.173	*-3.42****	-0.184	*-3.57****	-0.113	*-2.18***
13:00	-0.222	*-4.03****	-0.223	*-3.95****	-0.395	*-4.21****	-0.220	*-3.62****
13:15	-0.140	*-2.09***	-0.286	*-3.96****	-0.522	*-3.92****	-0.156	*-1.37*
13:30	0.440	*2.95****	-0.017	*-0.18*	-0.186	*-1.25*	0.361	*1.90**
13:45	-0.276	*-3.15****	-0.265	*-4.87****	-0.550	*-4.23****	-0.463	*-3.10****
14:00	-0.226	*-2.72****	-0.408	*-2.74****	-0.833	*-2.84****	-0.575	*-2.10***
14:15	-0.387	*-5.30****	-0.504	*-3.20****	-1.018	*-3.27****	-0.704	*-2.48***
14:30	-0.011	*-0.18*	-0.391	*-2.47***	-0.846	*-2.69****	-0.431	*-1.52*
14:45	0.034	*0.50*	-0.348	*-2.31***	-0.771	*-2.58****	-0.238	*-0.87*
15:00	0.149	*1.51*	-0.322	*-2.14***	-0.688	*-2.34***	0.002	*0.01*
15:15	-0.309	*-4.40****	-0.461	*-3.36****	-0.936	*-3.43****	-0.579	*-2.22***
15:30	-0.360	*-4.87****	-0.531	*-4.13****	-1.080	*-4.22****	-0.702	*-2.81****
15:45	-0.430	*-5.39****	-0.563	*-4.70****	-1.102	*-4.62****	-0.742	*-3.25****
16:00	-0.673	*-8.55****	-0.663	*-5.77****	-1.303	*-5.63****	-0.919	*-4.21****
16:15	-0.741	*-9.26****	-0.659	*-5.76****	-1.313	*-5.71****	-0.469	*-1.85**
Obs.	142,534		142,534		142,534		142,534	
R^2	69.80%		67.84%		50.85%		52.38%	

5.3.3 Informed Trading

Figure 5.4 depicts intraday patterns of 5-minute price impacts on the LSE, Chi-X, BATS and Turquoise. The figure shows that price impacts decrease for each 15-minute interval on all venues from Q1 to Q4. Similar to my findings on intraday quoted spreads, price impacts move more closely and show less variation over time. The highest fraction of informed trades takes place at the LSE in both quarters during most time of the trading day. However, intraday patterns of price impacts are very close across trading venues (even in Q1) compared to the previous measures.

In Q1, price impacts on all platforms decrease throughout the trading day, more quickly during the first hour of trading and then modestly for the rest of time. During the first hour of the trading day price impacts decrease by -31,2% on the LSE, by -25.8% on Chi-X, by -38.0% on BATS, and by -23.3% on Turquoise. As a consequence, trades convey most information during market opening and lose information content over the trading day. Investors on the LSE and Chi-X seem more informed than on BATS and Turquoise.

FIGURE 5.4: ***15-minute Snapshots of Intraday Price Impacts on the LSE, Chi-X, BATS, and Turquoise.*** *The figure shows average intraday 15-minute price impact snapshots of 69 FTSE 100 constituents on the LSE Chi-X, BATS, and Turquoise for Q1 and Q4 of 2009. I calculate price impacts as presented in Section 4.2.2 and obtain averages per day, stock, and 15-minute interval for each platform. Then I average all observations per 15-minute interval and platform over the two quarters.*



In Q4, price impacts on all platforms show a strong co-movement and still a continuing decrease over the trading day. Again, the largest decrease in price impacts can be attributed to the first trading hour. My regression results confirm the statistical significance of all presented developments.

Similar to McInish and Wood (1992), I find a positive relationship between this adverse selection risk measure (price impact) and quoted spreads. This contradicts the findings of Foster and Viswanathan (1993) who report increased adverse selection at both, market opening and closing. My results are rather in line with other market microstructure models that address the relationship of informed trading and liquidity (e.g., Glosten and Milgrom, 1985). They find that quoted spreads widen when the amount of information based trading increases. My results may indicate that informed traders benefit most from their informational advantage at market opening while the rest of the market is still relatively uninformed. Higher price uncertainty may thus represent a favorable opportunity for informed traders to act in order to conceal their superior knowledge.

Klussmann and Hautsch (2011) deliver another explanation. They show that the arrival of intraday news releases is clustered in the first half of the trading day and contributes to higher market uncertainty at market opening. While news releases peak at market opening they decrease gradually during the rest of the trading day (Klussmann and Hautsch, 2011, p. 324). This finding may also be connected to my intraday findings of price impacts. Apparently, the decrease of informed trading as presented in Figure 5.4 may result from a decreasing news arrival over the trading day.

TABLE 5.6: ***Intraday regression results: Price impacts.*** *I compare 69 FTSE100 stocks traded on the LSE, Chi-X, BATS, and Turquoise between January 5 to March 31, 2009 (1st quarter) and October 1 to December 30, 2009 (4th quarter). I use the regression model presented in equation 5.2 I report robust standard errors following Thompson (2011), t-statistics are presented in italic letters. '***' denotes significance at the 1% level, '**' at the 5% level, and '*' at the 10% level.*

	January to March 2009							
	LSE	t-stat.	Chi-X	t-stat.	BATS	t-stat.	TQ	t-stat.
Intercept	4.970	*21.74****	4.359	*16.27****	2.868	*5.26****	2.979	*8.48****
8:00	3.951	*8.48****	2.784	*4.63****	4.302	*4.16****	2.872	*5.22****
8:15	1.969	*5.64****	1.468	*3.40****	1.965	*2.14***	1.578	*2.89****
8:30	1.543	*3.64****	1.177	*2.42***	2.755	*4.03****	1.493	*2.59****
8:45	1.206	*3.13****	1.010	*2.74****	1.302	*1.83**	1.545	*2.61****
9:00	0.918	*2.80****	0.705	*1.81**	1.512	*3.03****	1.221	*2.27***
9:15	0.429	*1.36*	0.230	*0.69*	0.958	*1.75**	0.780	*1.97**
9:30	0.549	*1.94**	0.568	*1.90**	1.777	*3.26****	1.139	*2.81****
9:45	0.526	*1.65**	0.624	*1.73c*	1.500	*2.50***	1.236	*3.27****
10:00	0.289	*0.95*	0.178	*0.61*	1.559	*1.95**	0.581	*1.29*
10:15	0.018	*0.07*	0.510	*1.50*	1.524	*2.81****	0.711	*1.77**
10:30	-0.115	*-0.41*	0.260	*0.94*	1.388	*2.28***	-0.057	*-0.14*
10:45	-0.561	*-2.03***	-0.040	*-0.12*	1.242	*1.93**	0.343	*0.73*
11:00	-0.239	*-0.81*	0.094	*0.28*	0.712	*1.36*	0.713	*1.55*
11:15	0.040	*0.14*	0.153	*0.47*	0.997	*1.59*	0.344	*0.75*
11:30	-0.354	*-1.46*	-0.251	*-0.77*	0.557	*0.98*	0.229	*0.50*
11:45	-0.294	*-1.18*	-0.354	*-1.08*	1.096	*2.13***	-0.347	*-0.76*
12:15	-0.149	*-0.63*	-0.099	*-0.33*	0.413	*0.78*	0.037	*0.10*
12:30	-0.387	*-1.51*	-0.326	*-1.02*	0.941	*1.90**	-0.021	*-0.05*
12:45	-0.284	*-1.19*	-0.259	*-0.92*	0.373	*0.82*	0.087	*0.24*
13:00	-0.254	*-1.19*	-0.499	*-1.60*	0.375	*0.65*	0.026	*0.07*
13:15	-0.580	*-2.18***	-0.247	*-0.72*	0.258	*0.47*	0.154	*0.29*
13:30	-0.050	*-0.18*	-0.358	*-1.18*	0.155	*0.31*	-0.038	*-0.08*
13:45	-0.343	*-1.09*	-0.179	*-0.48*	0.099	*0.17*	0.541	*1.08*
14:00	-0.428	*-1.37*	-0.060	*-0.19*	0.852	*1.62*	0.038	*0.09*
14:15	-1.100	*-4.42****	-0.816	*-2.90****	-0.016	*-0.03*	-0.636	*-1.14*
14:30	-1.220	*-3.48****	-0.651	*-1.76**	-0.179	*-0.32*	-0.510	*-1.18*
14:45	-0.588	*-2.05***	-0.556	*-1.64*	0.941	*1.71**	-0.135	*-0.28*
15:00	-1.224	*-4.55****	-0.875	*-2.51***	0.159	*0.31*	-0.513	*-1.16*
15:15	-1.069	*-4.23****	-0.596	*-1.88**	0.704	*1.45*	-0.379	*-1.00*
15:30	-0.914	*-3.52****	-0.259	*-0.82*	-0.189	*-0.32*	-0.453	*-0.83*
15:45	-1.509	*-5.09****	-0.930	*-3.19****	0.088	*0.18*	-0.758	*-1.60*
16:00	-1.423	*-5.00****	-1.000	*-2.85****	-0.701	*-1.36*	-0.331	*-0.74*
16:15	-1.615	*-5.42****	-1.340	*-4.38****	-0.600	*-1.31*	-1.633	*-4.06****
Obs.	114,910		114,910		114,910		114,910	
R^2	11.48%		5.30%		1.37%		1.48%	

continued on the next page...

. . . continued from Table 5.6

	October to December 2009							
	LSE	t-stat.	Chi-X	t-stat.	BATS	t-stat.	TQ	t-stat.
Intercept	3.199	*22.12****	3.486	*30.38****	3.146	*21.86****	2.815	*16.37****
8:00	3.580	*10.93****	3.159	*11.27****	3.015	*8.82****	2.812	*9.56****
8:15	2.424	*8.61****	1.934	*9.31****	1.957	*7.51****	1.521	*8.00****
8:30	1.529	*6.58****	1.232	*6.08****	1.218	*4.43****	0.978	*4.06****
8:45	1.111	*5.72****	0.985	*7.46****	0.901	*4.25****	0.828	*4.21****
9:00	0.895	*4.35****	0.885	*4.67****	0.811	*3.67****	0.600	*2.34***
9:15	0.519	*2.91****	0.479	*3.01****	0.515	*2.90****	0.408	*1.80**
9:30	0.446	*2.21***	0.409	*2.78****	0.405	*1.86**	0.410	*1.81**
9:45	0.386	*2.18***	0.350	*2.29***	0.306	*1.69**	0.477	*2.34***
10:00	0.331	*1.42*	0.306	*1.86**	0.169	*0.70*	0.085	*0.39*
10:15	0.106	*0.63*	0.136	*1.02*	0.094	*0.70*	0.250	*1.19*
10:30	0.133	*0.74*	0.220	*1.40*	0.134	*0.66*	0.317	*1.63*
10:45	0.093	*0.64*	0.059	*0.52*	-0.068	*-0.44*	0.320	*1.85**
11:00	0.048	*0.29*	-0.045	*-0.37*	-0.031	*-0.22*	0.057	*0.34*
11:15	-0.090	*-0.61*	-0.103	*-0.87*	-0.282	*-1.87**	0.007	*0.04*
11:30	0.154	*0.96*	0.057	*0.47*	0.090	*0.50*	0.126	*0.55*
11:45	0.063	*0.35*	0.084	*0.56*	-0.141	*-0.83*	0.083	*0.39*
12:15	-0.003	*-0.02*	-0.142	*-1.15*	-0.164	*-1.25*	0.029	*0.17*
12:30	-0.013	*-0.07*	-0.038	*-0.29*	-0.124	*-0.75*	0.089	*0.44*
12:45	0.054	*0.35*	-0.036	*-0.27*	-0.041	*-0.24*	0.199	*0.96*
13:00	-0.266	*-1.95**	-0.181	*-1.65**	-0.252	*-1.66**	-0.173	*-1.00*
13:15	-0.614	*-2.39***	-0.324	*-1.70**	-0.607	*-3.20****	-0.198	*-0.74*
13:30	-0.545	*-2.57***	-0.296	*-1.51*	-0.714	*-4.27****	-0.682	*-2.76****
13:45	-0.075	*-0.37*	-0.044	*-0.27*	-0.097	*-0.55*	0.087	*0.36*
14:00	-0.183	*-1.04*	-0.126	*-0.88*	-0.403	*-2.45***	-0.257	*-1.27*
14:15	-0.602	*-3.66****	-0.445	*-3.38****	-0.515	*-2.82****	-0.499	*-2.70****
14:30	-0.743	*-4.37****	-0.364	*-2.48***	-0.497	*-3.19****	-0.458	*-2.08***
14:45	-1.075	*-5.29****	-0.512	*-3.45****	-0.660	*-3.76****	-0.779	*-3.63****
15:00	-0.699	*-3.96****	-0.431	*-2.96****	-0.519	*-3.51****	-0.767	*-3.61****
15:15	-0.870	*-4.51****	-0.434	*-2.70****	-0.635	*-3.61****	-0.571	*-2.79****
15:30	-0.897	*-5.34****	-0.484	*-3.73****	-0.653	*-3.78****	-0.670	*-3.45****
15:45	-0.921	*-5.59****	-0.450	*-3.07****	-0.722	*-4.02****	-0.498	*-2.48***
16:00	-0.964	*-6.07****	-0.621	*-4.64****	-0.784	*-4.35****	-0.562	*-2.66****
16:15	-1.069	*-5.43****	-0.851	*-5.76****	-1.040	*-5.81****	-0.820	*-3.94****
Obs.	136,382		136,382		136,382		136,382	
R^2	10.33%		8.80%		3.77%		2.94%	

5.4 Conclusion

MTFs have successfully captured a large fraction of European equity trading volume, especially in the UK. The market share of the LSE in blue chips decreased from almost 100.0% in 2007 to less than 60.0% at the end of 2009. I study the influence of increased market fragmentation on trading intensity and market quality under the Markets in Financial Instruments Directive (MiFID) over time and from an intraday perspective. My sample comprises 69 FTSE 100 stocks traded on the regulated market, the LSE, and the three largest MTFs, Chi-X, BATS, and Turquoise, between January and December 2009.

Over 2009, competition between the LSE and MTFs increases significantly as trading volume becomes more dispersed. Market shares strongly move away from the LSE which loses -17.2% to MTFs. Particularly Chi-X and BATS gain market shares during my observation period. Despite this increase in order flow fragmentation, I find improving market quality on all trading venues. Quoted and effective spreads decrease on all platforms during my observation period. This result suggests an increase in overall liquidity. Also other trading intensity and market quality measures indicate an improvement of overall market quality.

Order book depth increases significantly on the LSE while it remains unchanged on MTFs. This result may be connected to a stronger HFT activity on MTFs (Menkveld, 2011b). These market participants often cancel their limit orders immediately after placement to reduce associated economic risks. As a consequence, MTF order books are not as thick and may thus be more sensitive to sudden market distortions.

I obtain further insights into investor behavior by analyzing intraday patterns of trading volume, market shares, quoted spreads, and price impacts. To evaluate the impact of increased fragmentation on changes in intraday patterns over time, I focus on the first (Q1) and last quarter (Q4) of 2009. I find that intraday patterns for each analyzed measure converge across platforms from Q1 to Q4. This finding indicates that the market matures and grows closer together.

Intraday patterns of trading volume differ between the LSE and MTFs during both quarters. The LSE resembles a crude U-shape which is in line with theoretical predictions of Brock and Kleidon (1992) and empirical findings of other authors (e.g., Werner and Kleidon, 1996), while MTFs show increasing trading volume only in the second half of the trading day.[13] Trading volume increases in the afternoon on all venues which can be associated to the U.S. market opening. The analysis of intraday market shares reveals the importance of traditional exchanges in a fragmented market environment. My data suggests that investors prefer to trade on the regulated market at opening and closing, whereas trading switches to MTFs during the trading day. This result may indicate that market participants rely on the price formation process of regulated markets in periods of increased volatility and price uncertainty.

In contrast to theoretical predictions of Admati and Pfleiderer (1988) and Brock and Kleidon (1992) who expect U-shaped patterns for quoted spreads, my results indicate a reversed J-shape, i.e. increasing liquidity over the trading day which is also in line with other empirical studies (e.g., Cai et al., 2004). The underlying market structures may be one explanation for differences between theoretical and empirical evidence. The aforementioned theoretical models are based on quote-driven markets while I analyze order-driven markets. Intraday results for price impacts are in line with theoretical predictions of informed trading and liquidity (e.g., Glosten and Milgrom, 1985). My data suggest that the information content of trades declines quickly during the first trading hour and then falls continuously for the rest of the trading day. The decreasing information content of trades could also be attributed to a continuous decrease in intraday news arrival (Klussmann and Hautsch, 2011).

Overall, the results of this chapter may mitigate concerns of detrimental effects on market quality caused by increasing levels of order flow fragmentation. Yet, they also reveal that investors seem to have clear preferences on the choice of a trading venue depending on the market situation. Increased trading activity on the LSE at market opening and closing could be connected to increased price uncertainty. However, this could also be connected to market participants who are obliged to open or close their position at

[13]See Figure 3.1 for an overview of related empirical findings.

a regulated market (e.g., mutual funds, insurance companies, etc). To control for such a potential intradaily bias in trading activity triggered by certain market participants, I elaborate on this question in the next chapter from a more general perspective. I use a daily panel regression analysis to investigate whether there is an influence of price uncertainty on the order routing behavior of market participants.

Chapter 6

Back to the Roots - Market Fragmentation and Order Routing

"Technological innovations that enable high-speed, low-cost electronic trading systems are dramatically changing the structure of financial markets"

Barclay et al. (2003)

Chapter Overview. This chapter addresses empirically certain market conditions which may influence order routing behavior of market participants in a fragmented market environment. I also address the influence of order routing behavior on the information contribution of the four trading platforms to efficient prices.

6.1 Introduction

BEFORE the digitalization of equity trading, the predominant idea of how to organize an exchange was to centralize trading as much as possible. One important reason for this centralization were high search costs due to expensive information and communication technology. Intuitively, the idea of centralization seems logical in order to improve market quality by concentrating liquidity on one trading venue. This phenomenon is described by positive network externalities (Pagano, 1989b). The combination of high search costs and positive network externalities created high market entrance barriers for competitors.

This old-fashioned trading landscape changed quickly with the proliferation of electronic trading and regulatory changes. Today, a combination of computer algorithms and high speed internet connects trading venues worldwide within milliseconds. Prices on competing markets can be monitored and compared real-time and this at much lower costs compared to previous decades (Menkveld, 2011a). Along with regulatory changes, modern information and communication technology lead to the emergence of new fully electronic trading venues, so-called Multilateral Trading Facilities (MTFs). While traditional trading venues had to adapt to the digitalization of equity trading, MTFs were constructed from scratch to cope with this new era of electronic trading. Quickly, they have captured a significant share in European equity trading and pushed forward market fragmentation. The equity trading landscape in the UK has experienced increased competition from MTFs as one of the first within Europe. Until today, the FTSE 100 exhibits the largest level of fragmentation of all major European stock indices.[1]

Figure 2.1 displays the monthly share of electronic order book trading turnover of the LSE, Chi-X, BATS, and Turquoise from 2008 to 2012. The figure marks a continuous loss in turnover of the LSE, formerly Europe's largest trading venue also compared to other national exchanges.[2] According to the Federation of European Securities Exchanges

[1]See `http://fragmentation.fidessa.com/europe/` for an overview of fragmentation of European equity markets.
[2]See `http://www.fese.be/en/`.

(FESE), Chi-X captured the position as Europe's largest trading venue – including traditional exchanges – for the first time in August 2011.

Yet, the continuous fragmentation is reconsolidated by the emergence of a new group of market participants who emerged along with technological innovations and regulatory changes in equity trading. Algorithmic trading (AT), which can be defined as «*the use of computer algorithms to automatically make certain trading decisions, submit orders, and manage those orders after submission*» (Hendershott et al., 2011, p. 1) and in particular high frequency trading (HFT) which the Securities and Exchange Commission (SEC) refers to as «*...professional traders acting in a proprietary capacity that engage in strategies that generate a large number of trades on a daily basis[...]characteristics often attributed to proprietary firms engaged in HFT are[...]the use of extraordinarily high-speed and sophisticated computer programs for generating, routing, and executing orders [...]very short time-frames for establishing and liquidating positions[...]ending the trading day in as close to a flat position as possible*» connect the fragmented markets (U.S. Securities & Exchange Commission, 2010, p. 45). In combination with the use of smart order routing technologies, particularly HFT links markets via trades and quote updates within milliseconds.

Several scholars attribute many positive effects to the new trading platforms and market participants and their influence on overall market quality. Menkveld (2011b) argues that HFT are particularly active on MTFs. Through their trading strategies they act as new multi-venue market makers. He analyzes the introduction of Chi-X on the Dutch equity market where the MTF competes for market share against the traditional trading venue NYSE Euronext. He finds that HFT is active in both markets, but HFT accounts for the largest trading share on Chi-X. According to his paper, MTFs are particularly attractive to HFT for various reasons. On the one hand, HFT can act as multi-venue market makers due to speed sensitive environments which MTFs provide. On the other hand, MTFs offer lower fee structures. He argues that the emergence of HFT and MTFs create price pressure on traditional trading venues and the increased competition triggers positive welfare effects as for instance bid-ask spreads are reduced. Also Kirilenko et al. (2011) find that HFT account for a significant share of market making activity due to their trading strategies. They often use passive, liquidity providing orders to manage their target inventory levels (Kirilenko et al., 2011, p. 23).

Pagnotta and Philippon (2012) argue that – everything else being constant – all investors benefit from from faster trading through MTFs and HFT. Yet, they also state that different investors have different preferences on trading speed. Accordingly, these investors must value other attributes of a trading venue as well. Competing trading platforms may acknowledge this fact by addressing the particular needs of different trading clientele.

Other studies do not directly address HFT in their data sets but investigate the information contribution of MTFs to price efficiency compared to the traditional exchange. For example, Riordan et al. (2011) as well as Jung and Katzschner (2012) find in their UK and German data sets, respectively, that MTFs lead in price discovery. This indicates more informed trading on those venues. Also Hoffmann (2010) states that MTFs exhibit a significant higher share of private information compared to the traditional trading venues. These positive information effects on MTF price efficiency – and thus market quality – could be attributed to the increased HFT activity on MTFs. Foucault et al. (2012) also underline this idea in their findings. They argue that adverse selection is stronger when informed investors have a speed advantage because they can buy just in advance of positive news and sell in advance of negative news. MTFs clearly offer HFT the surrounding for the creation of speed advantages.

While several scholars argue that the appearance of MTFs and HFT have contributed to increased general market quality, there are also concerns. There is, for instance, an ongoing debate in the academic and finance world of how much trading speed is actually necessary and helpful (e.g., Bunge, 2011). Connected to alternative trading platforms and HFT, new events such as flash crashes or fake liquidity raise questions whether positive effects of MTFs and their HFT clientele are sustainable and helpful to the overall efficiency of a market. Most research papers address the influence of MTFs and HFT on market quality during normal market conditions. However, it is of great importance to investigate whether market services of a trading venue also function in periods of distress. A robust market structure should offer fair and orderly services at all times to market participants. In this respect, especially the sustainability of trading activity on

MTFs and finally their service provision in abnormal market conditions is of my major interest in this chapter.

Also other researchers point out that market participants may favor the traditional exchange over MTFs under certain market conditions. Storkenmaier et al. (2012) study the impact of public information on trading and market fragmentation in FTSE 100 stocks on the LSE and on Chi-X. They find that increased volatility attributed to increased public information release affects Chi-X market shares negatively, i.e., investors prefer to trade over the LSE during these periods.

Another important aspect which I address in this chapter is connected to the prevalent opinion of many practitioners, who argue that MTFs predominantly free-ride on the price formation of traditional exchanges. Also academic scholars provide evidence that MTF price formation may be heavily dependent on traditional exchanges. For instance, Gomber et al. (2012) analyze the effect of trading halts in DAX 30 constituents on the regulated market (Xetra) and an MTF (Chi-X). They state that the risk of missing circuit breakers on MTFs, which is due to regulatory difference between regulated markets and MTFs, represent a systemic risk to the market. They argue that in case of a trading halt at the traditional exchange, volatility may cascade to MTFs where it may trigger a flash crash like scenario. Yet, Gomber et al. (2012) find that if trading is halted on the regulated market, this is directly connected to an overall reduction of trading activity on the MTF. Their findings support the dependency of MTF price formation on regulated market prices.

Inspired through my findings in Section 5.3.1 and the concerns presented above, I analyze market conditions that may effect order routing and trading behavior of market participants in a fragmented market environment. As indicated in Figure 5.2, market participants seem to prefer trading on the traditional exchange at market opening and closing. These trading periods typically exhibit increased price uncertainty (e.g., Foster and Viswanathan, 1993) which might influence the investors' order routing. From an economic perspective, increased adverse selection risk on MTFs may be an explanation. As stated above, MTFs exhibit a significant higher share of traders with superior knowledge (Hoffmann, 2010; Riordan et al., 2011; Jung and Katzschner, 2012; Foucault et al., 2012). The risk of being adversely selected increases in periods of high market uncertainty (Admati and Pfleiderer, 1988). Therefore, uninformed traders might preferably trade over the LSE and route their orders there when uncertainty about a stock price is high. In turn, informed traders may follow the uninformed which might thus lead to increased price discovery on the LSE – relative to MTFs – and a defragmentation of the market in general.

I am also interested in HFT market making activity or – put differently – periods that may be connected to it (Menkveld, 2011b). The periods of my interest are typically connected to increased inventory risk which makes it uncomfortable for market makers to comply with their duty. HFT may act as market makers but they do not follow the regulatory requirements such as traditional market makers, i.e. they are not obliged to provide liquidity according to the rule book of a traditional exchange. Also regulators point out concerns that liquidity provision by HFT may not be granted as stable over time (U.S. Securities & Exchange Commission, 2010, p. 50). For this reason, I explore trading activity on the LSE, Chi-X, BATS, and Turquoise when market making becomes difficult. Unfortunately, my data set does not allow me to directly measure HFT (market making) activity on any trading venue. However, if HFT preferably trade on MTFs, market share of those trading platforms should significant decline when market making becomes generally more difficult as HFT can just drop out of the market.

For the empirical analysis in this part of my thesis, I calculate the consolidated order book of all four trading venues according to the methodology laid out in Section 4.1 during January 2 and December 31, 2009. The consolidated order book basically represents overall market activity since all four trading venues combined account for nearly 100% of non-OTC trading volume in FTSE 100 constituents. The final result is a stock-day panel from which I calculate all necessary variables which are explained in Section 4.2.

6.2 Volatility and intraday market shares

The intraday results in section 5.3.1 present a first indication that market participants seem to favor trading on the LSE during market opening and closing. These periods are typically characterized by an increased price uncertainty. Building on this first indication, I derive further graphical evidence to support this idea. Therefore, I look at the intraday market shares, which have been calculated in section 5.3. For all trading venues I calculate intraday 15-minute market shares per stock for the ten highest and ten lowest volatility days of 2009.[3] To identify the above mentioned specific volatility days, I use stock price volatility from the consolidated order book. Consequently, I compare market shares of each trading venue on these high/low volatility days with the the full sample market shares over 2009.

There are various ways how to calculate intraday volatility in a stock. Following Patton (2011), I briefly point out the three most common measures which are

1. squared daily returns,
2. the realized volatility measure, and
3. the intra-daily range.

The easiest and most intuitive way to calculate intraday volatility are squared returns. However, a significant shortcoming of this measure is that intraday price variation is neglected. Thus, an equity which exhibits large intraday price movements but closes with a similar price as the opening price would falsely exhibit a low volatility estimate. The two concepts of realized volatility and intra-daily range represent better alternatives which address the shortcoming of squared daily returns. Both measures have been intensively discussed and analyzed in market microstructure research. Realized volatility which is defined as

$$RV_t = \sum_{i=1}^{n} r_{i,t}^2 \ , \tag{6.1}$$

[3]Individual market shares represent the portion of trading volume on trading venue j compared to the overall trading volume of the consolidated market during each 15-minute interval.

i.e., the sum of n squared returns r of stock t computed from intraday transaction prices. It has been effectively used in academic research and Andersen et al. (2003) formally justify this measure. Its main advantage is that it is a more efficient estimator of the true volatility and has a lower variance compared to the squared daily returns.

Alizadeh et al. (2002) discuss in detail the advantages and disadvantages of realized volatility compared to the intra-daily range. They find that the realized volatility estimator becomes close to the true volatility if the sample of transaction prices is detailed enough, which indicates the necessity of intraday data. However, the main drawback of this volatility measure is its sensitivity to market microstructure noise. Due to the so called bid-ask bounce, the observed price is noisier than the true price. While the true price is the midpoint of the bid-ask spread, the observed price jumps up and down the midpoint by the half-spread depending on whether a trade is a buy or a sell. Thus, the realized volatility measure overestimates true volatility in the presence of transaction prices which are based on bid-ask spreads (Alizadeh et al., 2002).

Therefore, I choose the scaled intra-daily range (*IDR*) as presented by Patton (2011) for calculating price uncertainty.

$$IDR_t = \frac{1}{2\sqrt{(\ln(2)}} \ln\left(\frac{\max(p_i)}{\min(p_i)}\right) \tag{6.2}$$

A large advantage of this measure is connected to its calculation method. I only need two prices, the highest and the lowest of a trading day. Further, the IDR captures true volatility compared to the mean variance of a stock price. This measure has been widely used in finance literature for many years and was first presented by Parkinson (1980). The scaling factor ($\frac{1}{2\sqrt{(\ln(2)}}$) assures the unbiasedness given a Brownian motion of stock prices (Patton, 2011, pp.4-5). By choosing the IDR, I calculate an unbiased estimator of true volatility.[4]

Figures 6.1, 6.2, 6.3, and 6.4 reveal that the LSE exhibits a larger intraday market share on high volatility days. Consequently, LSE's market share is lower on trading days with less price uncertainty, i.e., regular or low volatility days. In comparison to the

[4] For robustness, I also calculate volatility days for all trading venues by using realized volatility. Results are identical to the IDR volatility measure for both quarters.

LSE, the three MTFs show a reciprocal picture. Apparently, market participants seem to be more active on these platforms when price uncertainty is lower. On high volatility days MTF market share decreases. This pattern is clearly visible for Chi-X and BATS. Turquoise shows a different picture. Surprisingly, Turquoise shows a similar pattern than the LSE for intraday market shares until 13:00. One possibility for this finding might be the merger of LSE's dark pool activity with Turquoise during 2009. Yet, this is merely speculation.

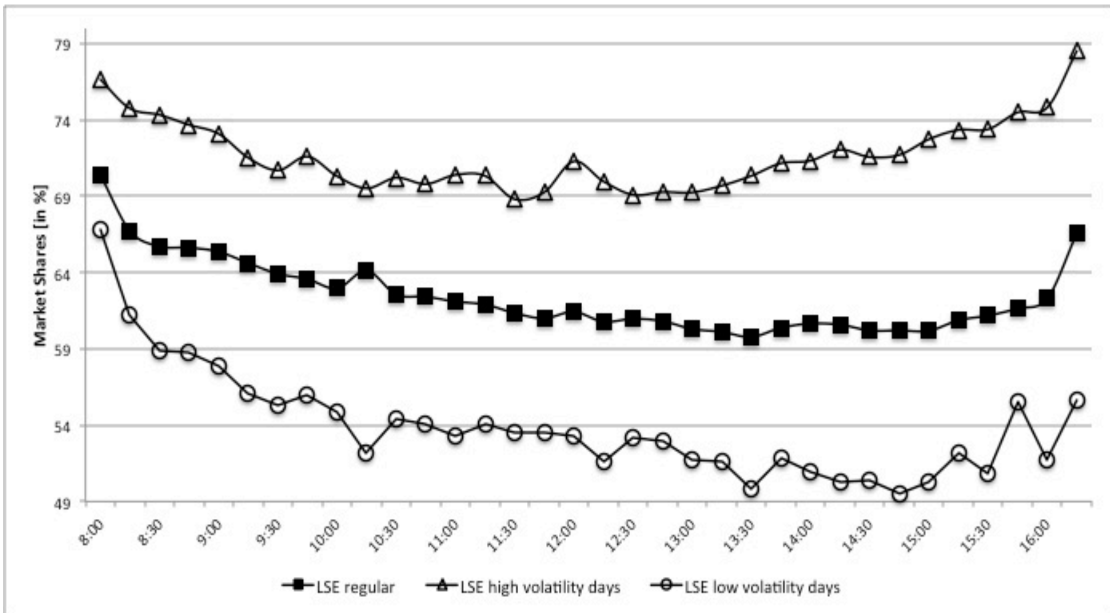


FIGURE 6.1: ***Intraday market shares of the LSE, for regular, high, and low volatility days in 2009.*** *I calculate intraday 15-minute market shares per stock according to Section 4.2.2 for the 10 highest and 10 lowest volatility days of 2009. I compare these graphical results with the regular average 15-minute market shares per stock of the overall sample of 244 trading days.*

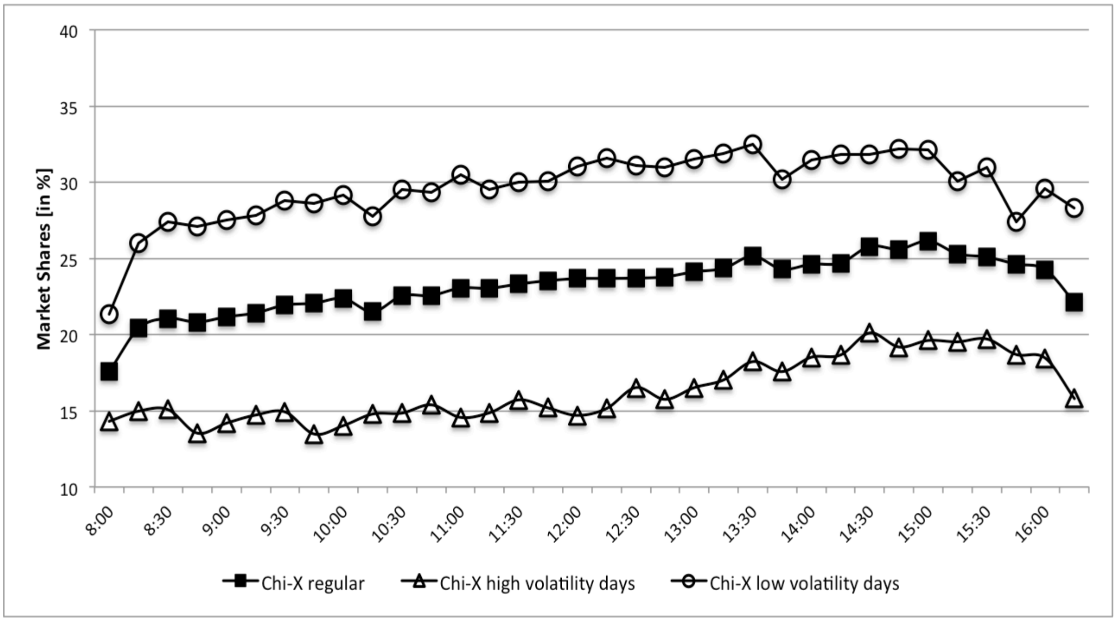


FIGURE 6.2: ***Intraday market shares of Chi-X, for regular, high, and low volatility days in 2009.*** *I calculate intraday 15-minute market shares per stock according to Section 4.2.2 for the 10 highest and 10 lowest volatility days of 2009. I compare these graphical results with the regular average 15-minute market shares per stock of the overall sample of 244 trading days.*

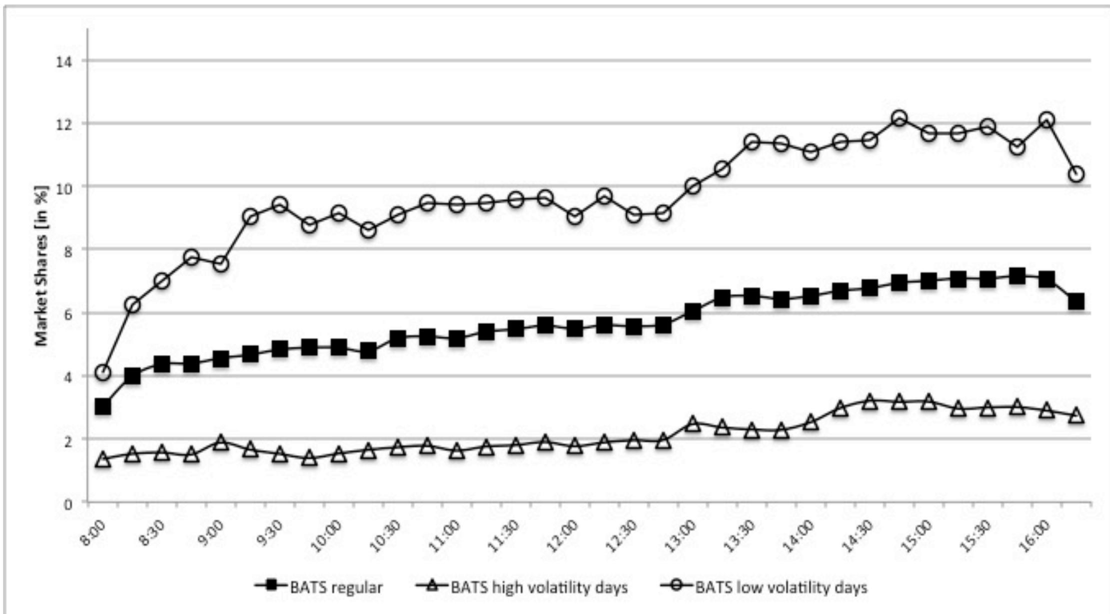


FIGURE 6.3: ***Intraday market shares of BATS, for regular, high, and low volatility days in 2009.*** *I calculate intraday 15-minute market shares per stock according to Section 4.2.2 for the 10 highest and 10 lowest volatility days of 2009. I compare these graphical results with the regular average 15-minute market shares per stock of the overall sample of 244 trading days.*

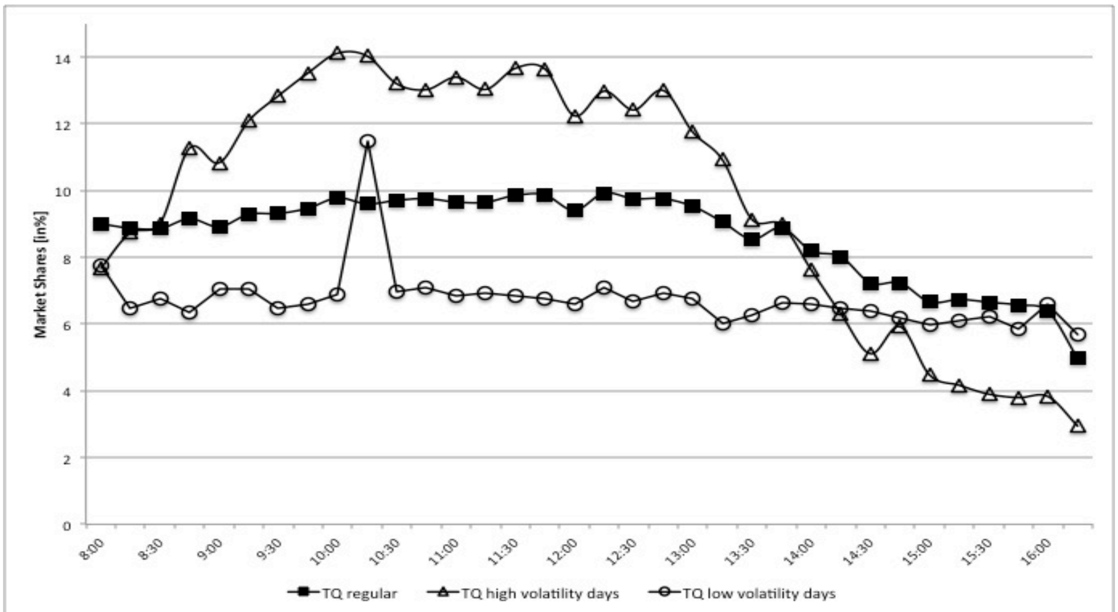


FIGURE 6.4: ***Intraday market shares of Turquoise, for regular, high, and low volatility days in 2009.*** *I calculate intraday 15-minute market shares per stock according to Section 4.2.2 for the 10 highest and 10 lowest volatility days of 2009. I compare these graphical results with the regular average 15-minute market shares per stock of the overall sample of 244 trading days.*

6.3 Econometric Modeling

Apparently, market participant's uncertainty about stock prices seems to have an effect on their order routing behavior. Besides graphical evidence, I deliver first econometrical proof from an intraday perspective in Section 5.3.1. Here, my results indicate that market participants seem to trade more actively on the LSE at market opening and closing, which are typically associated with higher price uncertainty due to new information arrival or portfolio rebalancing. Yet, these results may be influenced by various other factors as for instance the need of certain market participants to close their books with reference prices coming from a regulated market. Therefore, I develop econometric models which analyze these relations rather over time instead of intraday. My goal is to find out whether high price uncertainty of market participants influences market fragmentation negatively. Connected to this, I also investigate the effect of increased price uncertainty on price discovery. For this, I model price discovery of each trading venue via information shares according to Hasbrouck (1995) as outlined in Section 4.2.3.

Besides price uncertainty, I investigate further effects and market conditions which may influence market fragmentation and thus the order routing behavior of market participants. Therefore, I control on an individual stock level for several other potential factors such as liquidity, trading volume, market capitalization, and the average price of a stock. Additionally, I create a proxy for difficult market making days as outlined in Section 4.2.4. I expect MTF trading activity to be considerably lower on these days, due to a potential withdrawal from HFT.

The use of smart order routing technologies enable market participants to trade on all four trading venues in parallel. For this reason, I derive overall trading volume in a stock, effective spreads, and the average price for a stock from the consolidated order book which I create from all four single order books.[5]

I develop two OLS regression models with robust clustered standard errors, according

[5]See Section 4.1 for details about the creation of the consolidated order book.

to Thompson (2011)[6]. The first model measures the influence of the above outlined factors on (a) market fragmentation or (b) individual market shares of the LSE, Chi-X, BATS, and Turquoise. I model market fragmentation as the volume share of stock i on day t traded on other markets (MTFs) than the traditional exchange (LSE), i.e., it represents the relative MTF trading share.[7]

Regression Model I:

$$\begin{aligned} measure_{i,t/j} &= \alpha_0 + \beta_1 HighVola(C)_{i,t} + \beta_2 MarketMaking_{i,t} + \beta_3 Eff.Spr(C)_{i,t} \\ &+ \beta_4 ln\ Vol(C)_{i,t} + \beta_5 ln\ Mcap_{i,t} + \beta_6 ln\ Avg\ Pr(C)_{i,t} + \epsilon_{i,t} \end{aligned} \tag{6.3}$$

where $measure_{i,t/j}$ represents either (a) the MTF traded volume share of a stock i on day t (given that the measure represents fragmentation) or (b) the market share of stock i on day t on trading venue j.[8] These measures are modeled as a function which includes:

- the dummy variable $HighVola(C)_{i,t}$ which is 1 if a stock's price uncertainty measured by the intra-daily volatility range belongs to the highest 1, 3, or 5% volatility days of the consolidated order book and 0 otherwise,[9]
- the dummy variable $MarketMaking_{i,t}$ which is 1 if a trading day t has been classified as a difficult market making day on any of the trading venues as explained in Section 4.2.4 and 0 otherwise, and
- other market (control) factors: The effective spread $Eff.Spr(C)_{i,t}$ as a measures of overall market liquidity, the logarithm of daily trading volume $ln\ Vol(C)_{i,t}$, the

[6]Clustered standard errors according to Thompson (2011) control simultaneously for correlations in the regression residuals across two dimensions. In my data panel, residuals might be correlated across sample firms (firm effect) and across time (time effect). Clustering for those two dimensions allows me thus to obtain robust standard errors. For details on the methodology, see Thompson (2011).

[7]Compare Section 4.2.1.

[8]I run the regression model separately for LSE, Chi-X, BATS, or Turquoise market shares or the fragmentation variable.

[9]I deliberately select the intra-daily range to capture the full range of daily volatility in a stock rather than the standard deviation around mean prices, see also Section 6.2. To check for robustness, I also estimate the regression model with other volatility indicators. Firstly, I use realized volatility on the individual stock level which delivers identical results as the IDR. Secondly, I estimate the model with the VFTSE as an indicator of overall market uncertainty on a macro level. The VFTSE index captures implied volatility embedded in prices of FTSE 100 options and serves thus as a perfect indicator for overall expected market uncertainty. The results of overall market uncertainty are similar to the results of price uncertainty on the stock level. Therefore, I do not discuss these results in detail.

logarithm of a stock's market capitalization $ln\ Mcap_{i,t}$, and the logarithm of the daily average price of a stock $ln\ Avg\ Pr(C)_{i,t}$ ("C" stands for the consolidated order book).

Descriptive statistics in Section 6.4.1 indicate a positive relationship between market capitalization and fragmentation, which means that higher market cap stocks are being traded more actively on MTFs. Therefore, I run a separate regression as a robustness variation of Regression Model I, where I replace the market capitalization variable with dummy variables for highest and lowest market cap quintiles.

Several scholars have outlined that MTFs lead in price discovery (e.g., Riordan et al., 2011; Jung and Katzschner, 2012). Therefore, my second regression model measures the influence of price uncertainty and the other above outlined factors on Hasbrouck (1995) information shares.

Regression Model II:

$$\begin{aligned} measure_{i,t,j} &= \alpha_0 + \beta_1 HighVola(C)_{i,t} + \beta_2 MarketMaking_{i,t} + \beta_3 Eff.Spr(C)_{i,t} \\ &+ \beta_4 ln\ Vol(C)_{i,t} + \beta_5 ln\ Mcap_{i,t} + \beta_6 ln\ Avg\ Pr(C)_{i,t} + \epsilon_{i,t} \end{aligned} \tag{6.4}$$

where $measure_{i,t,j}$ represents detrended Hasbrouck (1995) information shares of stock i on day t on trading venue j.[10] All other components of the regression model are equal to Regression Model I.

[10] Also information shares of the LSE and Chi-X seem to follow a trend over time (see Figure 4.3). While the LSE exhibits a higher contribution to price efficiency at the beginning of 2009 this share decreases over time while Chi-X and TQ information shares increase (see Table 6.1). Therefore, I also detrend trading venues' information shares – assuming a deterministic trend – by taking the residuals from a linear regession model of the relevant measures on time.

6.4 Regression Results

6.4.1 Descriptive Statistics

I present descriptive statistics for endogenous and exogenous variables of Regression Models I and II in Table 6.1 over the full data sample as well as during Q1 and Q4 to get an idea how the variables developed over time. The table lists averages across all stocks for the endogenous variables fragmentation (*Frag*) and Hasbrouck (1995) information shares of each trading venue (e. g. , *InfoShare LSE*). The table also includes averages across all stocks for the exogenous variables volatility (*IDR(C)*), effective spreads (*Eff.Spread(C)*), trading volume (*Trad.Vol.(C)*), market capitalization (*Mcap*), and the average price (*Avg.Price(C)*).[11]

As presented in the previous chapter, fragmentation increases over time along with liquidity. While trading in UK equities was fragmented on average by 28.2% in Q1 this ration increased to 45.7% in Q4. Effective Spreads decrease by roughly 2 bps from Q1 to Q4. Price uncertainty was higher in Q1 with a mean intraday volatility of 3.4% (1.6% in Q4). A first glance on the trading venues information shares (full sample) reveals that Chi-X on average seems to contribute most to overall price discovery with 52.4%. While MTF information shares seem to grow over time, e. g. , Chi-X from 41% in Q1 to 60.2% in Q4, LSE's contribution to price discovery decreases from Q1 to merely 26.9% in Q4.[12] This finding is in line with other studies who argue that prices often "move first" on MTFs (e.g., Riordan et al., 2011).

Table 6.2 presents first descriptive insights into the correlation of various parameters of Regression Models I and II over the full sample period. The table hints to a negative correlation between overall market fragmentation and volatility (IDR) as well as effective spreads. This on the one hand, may point to a reduction of MTF trading activity

[11] For the descriptive statistics part, I use regular intra-daily volatility (IDR) as proposed in Section 6.2 instead of dummy variables for the highest 1%, 3%, or 5% volatility days (HighVola). I also use actual instead of logarithmic values for trading volumes, market caps and average prices. For brevity, I do not list individual market shares of the four trading venues as they have already been discussed in detail in Section 5.2. (C) indicates that this measures has been created from the the consolidated order book.

[12] See also Figure 4.3 for a graphical overview of information shares during 2009.

TABLE 6.1: ***Descriptive statistics: Variables of regression model I & II*** *The table presents endogenuous and exogenuous variables of Regression Model I & II. For descriptive statistics, I use regular intra-daily volatility as proposed in Section 6.2 instead of dummy variables for the highest 1%, 3%, or 5% volatility days. I also use actual instead of logarithmic values for trading volumes, market caps and average prices. For brevity, I do not list individual market shares of the four trading venues as they have already been discussed in detail in Section 5.2. Dummy variables for difficult market making days are not included in this table. (C) indicates that this measures has been created from the the consolidated order book.*

	Full (16,836 Obs.)		Q1 (4,140 Obs.)		Q4 (4,209 Obs.)	
	Mean	StdDev	Mean	StdDev	Mean	StdDev
Frag	0.367	0.074	0.282	0.022	0.457	0.031
InfoShare LSE	0.361	0.151	0.480	0.156	0.269	0.121
InfoShare ChiX	0.524	0.165	0.410	0.181	0.602	0.139
InfoShare BATS	0.068	0.065	0.082	0.074	0.081	0.060
InfoShare TQ	0.049	0.054	0.029	0.043	0.049	0.044
IDR(C)	0.023	0.021	0.034	0.029	0.016	0.009
Eff.Spread(C) [bsp]	3.609	2.004	4.841	2.901	2.806	1.068
Trad.Vol.(C) [in kGBP]	5,449	6,304	5,499	6,560	5,753	6,295
Mcap [in kGBP]	19,343	26,719	16,430	23,885	22,610	30,399
Avg. Price(C) [GBP]	780.62	667.81	674.93	582.39	909.12	761.34

once volatility increases, while fragmentation on the other hand seems to foster overall liquidity.

In the regressions, I also control for market capitalization and the average price. With regard to market capitalization, I am particularly interested whether fragmentation affects different sized companies in the same way. The correlation coefficients indicate that market fragmentation is positively associated with market capitalization of a stock. This might indicate that large cap stocks are preferably traded over MTFs.

Table 6.2 reveals a further interesting insight with regard to the trading venues information contribution to efficient prices. The correlation between LSE information shares and volatility is positive. Contrarily, the information shares of all MTFs show negative correlations with volatility. This preliminary finding may support the idea that trading activity concentrates at the traditional exchange particularly in abnormal market situations.

TABLE 6.2: ***Correlation: Variables of regression models I & II*** *The table shows pearson correlation coefficients between endogenuous variables Fragmentation and individual information shares of each trading venue InfoShare and the exogenous variables Volatility, Effective Spread, Trading Volume, Market Capitalization, and Average Price.*

Pearson Correlation Coefficients – Full Sample	Frag	InfoShare LSE	InfoShare ChiX	InfoShare BATS	InfoShare TQ	IDR(C)	Eff.Spread(C)	Trad.Vol.(C)	Mcap	Avg. Price(C)
Frag	1.000	-0.425	0.361	-0.049	0.146	-0.324	-0.381	-0.011	0.082	0.121
		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.169	<.0001	<.0001
InfoShare LSE		1.000	-0.864	0.001	-0.161	0.199	0.270	0.011	-0.075	-0.122
			<.0001	0.856	<.0001	<.0001	<.0001	0.151	<.0001	<.0001
InfoShare ChiX			1.000	-0.391	-0.175	-0.101	-0.241	0.083	0.065	0.118
				<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
InfoShare BATS				1.000	0.000	-0.089	0.010	-0.130	0.015	-0.014
					0.999	<.0001	0.186	<.0001	0.058	0.069
InfoShare TQ					1.000	-0.146	-0.028	-0.133	-0.006	-0.004
						<.0001	0.000	<.0001	0.421	0.560
IDR(C)						1.000	0.503	0.114	-0.090	-0.140
							<.0001	<.0001	<.0001	<.0001
Eff.Spread(C)							1.000	-0.292	-0.378	-0.314
								<.0001	<.0001	<.0001
Trad.Vol.(C)								1.000	0.697	0.267
									<.0001	<.0001
Mcap									1.000	0.370
										<.0001
Avg. Price(C)										1.000

6.4.2 Regression Results

In the following section, I present the results of my Regression Models I and II. For both models, I use detrended endogenous variables as explained in Section 4.2.1 and I use logarithmic values of trading volumes, market capitalizations, and average stock prices. I also calculate robust clustered standard errors according to Thompson (2011) for both models.

Price Uncertainty and Market Fragmentation I use the volatility of the consolidated order book – measured by the IDR – to represent market participants' price uncertainty of a stock. My intention is to analyze the order routing behavior of market participants under abnormal market conditions. Therefore, I create dummy variables for the highest 1%, 3%, and 5% of all volatility observations of my IDR measure (*HighVola(C)*). Table 6.3 displays results of Regression Model I for all three volatility categories – Panel A (1%), Panel B (3%), and Panel C (5%) – from the yearly sample with a total of 16,836 observations.[13] I find a significant negative relationship between market fragmentation ($Frag_{i,t}$) and increased price uncertainty (*HighVola(C)*) for the 1% and 3% of the highest volatility observations. This evidence clearly indicates decreasing MTF trading volumes with increasing price uncertainty.

The table also shows the impact of price uncertainty on individual market shares of the LSE, Chi-X, BATS, and Turquoise. I find a significant positive relationship between price uncertainty and LSE market shares for the highest 1% and 3% volatility observations. All MTFs exhibit negative coefficients for the 1% dummy where BATS and Turquoise coefficients are highly significant. This shows on a more detailed level that market participants preferably route their orders to the LSE in trading periods of increased price uncertainty while MTFs lose order flow under such circumstances. While BATS and Turquoise experience significant losses in market shares with increasing volatility, the effect on Chi-X seems not as evident. Chi-X exhibits no significant losses for any of the three volatility categories. In general, the effect is less evident

[13] I also run the regression for over Q1 and Q4 as a robustness check. Results for these periods are similar to the yearly sample and thus confirm the robustness of my model over time.

TABLE 6.3: ***Regression Model I: Regression results.*** *I compare 69 FTSE100 stocks traded on the LSE, Chi-X, BATS, and Turquoise between January 5 to December 30, 2009. I use the regression model presented in equation 6.3 with detrended endogenuous variables (per stock i and day t) and logarithmic values of trading volumes, market capitalizations, and average stock prices. I report robust standard errors following Thompson (2011), t-statistics are presented below the regression coefficients in italics. '***' denotes significance at the 1% level, '**' at the 5% level, and '*' at the 10% level.*

Panel A						
	2009 Full Sample					
	High Vola(C) 1%	Market Making	Eff. Spread(C)	Ln Vol(C)	Ln Mcap	Ln AvPr(C)
$Frag_{i,t}$	-0.0159 ***	-0.0137 ***	-0.0017 ***	-0.0104 ***	0.0060 ***	-0.0013 **
	-2.97	*-4.08*	*-3.50*	*-4.05*	*3.55*	*-1.99*
MkShare $LSE_{i,t}$	0.0159 ***	0.0137 ***	0.0017 ***	0.0104 ***	-0.0060 ***	0.0013 **
	2.97	*4.08*	*3.50*	*4.05*	*-3.55*	*1.99*
MkShare $ChiX_{i,t}$	-0.0026	-0.0100 ***	-0.0012 ***	-0.0066 ***	0.0035 ***	-0.0011 **
	-0.74	*-4.20*	*-3.51*	*-4.27*	*3.54*	*-2.46*
MkShare $BATS_{i,t}$	-0.0035 ***	-0.0037 ***	0.0000	-0.0013 *	-0.0008	0.0001
	-2.58	*-3.48*	*0.26*	*-1.67*	*-1.34*	*0.51*
MkShare $TQ_{i,t}$	-0.0098 ***	0.0000	-0.0005	-0.0052 ***	0.0033 ***	-0.0003
	-2.77	*0.01*	*-1.59*	*-4.41*	*3.88*	*-0.98*

Panel B						
	2009 Full Sample					
	High Vola(C) 3%	Market Making	Eff. Spread(C)	Ln Vol(C)	Ln Mcap	Ln AvPr(C)
$Frag_{i,t}$	-0.0070 **	-0.0138 ***	-0.0018 ***	-0.0103 ***	0.0059 ***	-0.0013 **
	-1.99	*-4.09*	*-3.59*	*-3.94*	*3.45*	*-2.01*
MkShare $LSE_{i,t}$	0.0070 **	0.0138 ***	0.0018 ***	0.0103 ***	-0.0059 ***	0.0013 **
	1.99	*4.09*	*3.59*	*3.94*	*-3.45*	*2.01*
MkShare $ChiX_{i,t}$	0.0008	-0.0100 ***	-0.0013 ***	-0.0067 ***	0.0036 ***	-0.0011 **
	0.33	*-4.21*	*-3.74*	*-4.28*	*3.54*	*-2.41*
MkShare $BATS_{i,t}$	-0.0016	-0.0037 ***	0.0000	-0.0013 *	-0.0008	0.0001
	-1.63	*-3.51*	*0.24*	*-1.65*	*-1.36*	*0.50*
MkShare $TQ_{i,t}$	-0.0062 ***	0.0000	-0.0005	-0.0050 ***	0.0032	-0.0003
	-2.85	*-0.02*	*-1.40*	*-4.18*	*3.73*	*-1.06*

continued on the next page...

. . . continued from Table 6.3

Panel C						
	2009 Full Sample					
	High Vola(C) 5%	Market Making	Eff. Spread(C)	Ln Vol(C)	Ln Mcap	Ln AvPr(C)
$\text{Frag}_{i,t}$	-0.0048	-0.0137 ***	-0.0018 ***	-0.0104 ***	0.0059 ***	-0.0013 **
	-1.50	*-4.07*	*-3.71*	*-3.89*	*3.39*	*-1.98*
MkShare $\text{LSE}_{i,t}$	0.0048	0.0137 ***	0.0018 ***	0.0104 ***	-0.0059 ***	0.0013 **
	1.50	*4.07*	*3.71*	*3.89*	*-3.39*	*1.98*
MkShare $\text{ChiX}_{i,t}$	0.0007	-0.0101 ***	-0.0013 ***	-0.0067 ***	0.0036 ***	-0.0011 **
	0.34	*-4.22*	*-3.72*	*-4.24*	*3.51*	*-2.42*
MkShare $\text{BATS}_{i,t}$	-0.0013	-0.0037 ***	0.0000	-0.0014 *	-0.0008	0.0001
	-1.57	*-3.49*	*0.25*	*-1.66*	*-1.37*	*0.51*
MkShare $\text{TQ}_{i,t}$	-0.0042 **	0.0000	-0.0005	-0.0050 ***	0.0032 ***	-0.0003
	-2.42	*0.01*	*-1.58*	*-4.16*	*3.66*	*-1.01*

for all trading venues for lower volatility categories, i.e., the 3% and 5% IDR dummy. In other words, if trading conditions normalize, fragmentation increases and trading activity spreads to MTFs.

Overall, these results confirm my intraday findings of Chapter 5. Trading activity does concentrate on the traditional exchange when price uncertainty is high (e.g., at market opening or closing). As potential causes for the intraday patterns I envision: (a) the need of certain market participants to open and close their positions on a regulated market due to regulatory requirements (e.g., mutual funds) or (b) increased adverse selection risk on MTFs which drives investors to route their orders to the LSE during these periods.

The results of this chapter deliberately neglect intradaily variations of trading activity but still find a negative relationship between volatility and market fragmentation. This points thus rather to option (b). It seems that a concentration of trading activity on a single trading venue – no matter if intraday or interday – is more influenced by adverse selection. Several scholars state that investors trading on MTFs exhibit a higher degree of private information or react quicker upon public information (e.g., Hoffmann, 2010; Riordan et al., 2011). Additionally, scholars state that the adverse selection risk increases when informed traders have a speed advantage (Foucault et al., 2012). Both findings point to higher adverse selection risk at MTFs. Increased volatility widens the informational gap between informed and uninformed traders even further and trading on MTFs may thus become particularly unpleasant for market participants. This may explain potential shifts in market particiants' order routing towards the traditional exchange. Further reasons may be given through the complementary services that the traditional exchange offers – besides a less speed-sensitive environment. Market participants may value additional services of traditional exchanges, such as circuit breakers, real market makers, or an independent market surveillance, as particularly important during abnormal trading periods.

Liquidity and Market Fragmentation I measure a stock's market wide liquidity by effective spreads of the consolidated order book (*Eff. Spread(C)*). I find a significant negative relationship between effective spreads and fragmentation as stated in Table 6.3. This reveals that liquidity and fragmentation are positively connected. Contrarily, increasing spreads (decreasing liquidity) lead to a reduction in MTF trading volume. Put differently, in normal market conditions when overall trading activity is high, market participants are more willing to route their orders to MTFs. This finding can be explained by network externalities, as shown by Pagano (1989a). He states that network externalities may cause a liquidity spiral. MTFs may be able to absorb more liquidity with an overall rising level of trading activity. Market participants who choose to trade over the LSE due to insufficient liquidity on MTFs will potentially re-route their orders with rising market liquidity.

Table 6.3 indicates that Chi-X is the only MTF that significantly benefits from rising liquidity levels. The LSE exhibits a significant positive relationship between effective spreads and its market share. This means that the LSE is the only trading venue that attracts increasing trading volume if overall liquidity drops. Market participants thus seem to favor the LSE given a lower liquidity trading environment.

Trading Volume, Market Capitalization, and Market Fragmentation Table 6.3 reveals a significant negative relationship between the daily traded volume of a stock (*Ln Vol(C)*) and market fragmentation. With regard to individual market shares, I find significant negative relationships between daily traded volume and MTF market shares, while the LSE shows a significant positive relation. These findings may be explained by the risk of an adverse price change on a market with little – or less – power to absorb large orders (Pagano, 1989a). If a trader has a large order, or a large position, to place in the market, he will always choose the "thickest" market, according to order book depth.[14] The order can thus be executed at a better price and with a lower risk of an adverse price change. As indicated in the table, market participants route large trading volumes preferably to the LSE. In Chapter 5, I pointed out that depth on the LSE may be less sensitive to unexpected market deteriorations as its order book is thicker

[14] My results do not take into account different order size categories. Yet, larger daily trading volume is correlated with large order sizes. However, a refinement of this variable with different order size categories, may be an interesting step for future research.

(See also Table 5.2). Another reason for the routing of larger volumes to the LSE may be that LSE's liquidity provision is more reliable. Due to ultra fast order submissions and cancellations of HFT, liquidity levels on MTFs may not be as stable compared to the traditional exchange.

Market Capitalization. The results of table 6.3 clearly indicate a positive relationship between market capitalization (*Ln Mcap*) and market fragmentation. For individual market shares, market capitalization shows a significantly positive correlation with Chi-X as well as Turquoise and a negative correlation with LSE market shares. To analyze this relationship in more detail, I create two additional dummy variables by clustering market capitalization into quintiles. I replace the market capitalization variable in Regression Model I with two market capitalization dummies, (a) representing the lowest and (b) representing the highest market capitalization quintile. Table 6.4 presents results for the two market capitalization dummies on individual market shares.[15]

As already expected from the general market capitalization coefficient in Table 6.2, there is a difference between trading activity of large and small cap stocks on MTFs and the LSE. Large cap stocks seem to be preferably traded on MTFs. The high market cap dummy coefficients are positive for all three MTFs while the LSE market shares exhibits a significant negative relationship to large cap stocks. However – not as significant – the table shows a reciprocal picture for small cap stocks. These findings are particularly interesting because they add to the institutional differences between the LSE and MTFs. Usually, large cap stocks exhibit high liquidity levels which can be traded without additional liquidity provision over the electronic limit order books. Small cap stocks, however, are often less liquid and the supplementary liquidity provision of a (LSE) market maker may come in handy, if necessary.

MTFs do not offer supplementary liquidity provision through market makers. Yet, several scholars argue that HFT may take over these market making activities on MTFs by instantly providing liquidity via their limit order strategies (e.g., Menkveld, 2011b; Kirilenko et al., 2011). Others support this view and argue that HFT particularly pro-

[15]Results of other coefficients are identical to Regression Model I. Therefore, I only present coefficients for the two market cap quintiles.

TABLE 6.4: ***Regression Model I: Market capitalization.*** *I compare 69 FTSE 100 stocks traded on the LSE, Chi-X, BATS, and Turquoise between January 5 to December 30, 2009. I use the regression model presented in equation 6.3 with detrended endogenuous variables (per stock i and day t) and logarithmic values of trading volumes, market capitalizations, and average stock prices. However, for the results of this table, I replace the market cap variable of equation 6.3 with two dummy variables for the (a) lowest quintile and (b) highest quintile of all market cap observations. Results of other coefficients are identical to Regression Model I. Therefore, I only present coefficients for the two market cap dummies. I report robust standard errors following Thompson (2011), t-statistics are presented below the regression coefficients in italics. '***' denotes significance at the 1% level, '**' at the 5% level, and '*' at the 10% level.*

	2009 Full Sample			
	(a) Mcap low		(b) Mcap high	
MkShare $LSE_{i,j}$	0.0032		-0.0066	***
	1.51		*-2.75*	
MkShare $ChiX_{i,j}$	-0.0018		0.0050	***
	-1.38		*3.07*	
MkShare $BATS_{i,j}$	-0.0005		0.0014	
	-0.70		*1.60*	
MkShare $TQ_{i,j}$	-0.0019	*	0.0030	**
	-1.79		*2.39*	

vides liquidity when it is expensive, i.e., when spreads are wide and therefore needed (Hendershott and Riordan, 2009, p. 4).

However, even if these supplementary functions may be provided by HFT, this does not imply that they can be counted on in any circumstances. One of my major research questions addresses the reliability of HFT liquidity provision in a fragmented market environment. Institutional differences between a traditional exchange and MTFs in the service provision may herein play an important role. While HFT may instantly decide to halt liquidity provision, traditional market makers are obliged to continue their duty according to the exchange's rules and requirements.

Market Making and Market Fragmentation To test the reliability of HFT market making strategies, I address a scenario that poses serious problems to liquidity providers. I create dummy variables for trading days which can be considered as difficult in terms of market making. These days are typically characterized by a long or short bias of market participants. Once a trading day exhibits continuously increasing or decreasing stock prices, it is harder for market makers to control their inventory. A major goal for a market maker is to close his book with a zero position in order to not face any overnight exposure. The same accounts for most HFT trading strategies (Brogaard et al., 2012). Thus, long or short biased trading days are associated with higher inventory risk and thus potential trading losses. Typically, HFT is not required to provide liquidity by a regulated market's rule book. Therefore, I expect HFT activity to be considerably lower during these days. Since HFT accounts for a large share of MTF trading volume, I consequently expect the associated trading volume on MTFs to be significantly lower during these difficult market making days.

Table 6.3 displays regression results of my difficult market making dummies (*Market Making*). As expected, I find a significant negative relationship between difficult market making days and market fragmentation. In particular, on difficult market making days, market shares are lower on Chi-X and BATS while they positively contribute to LSE's market share. My findings support the idea that HFT market making activity is negatively influenced as soon as it becomes difficult to control inventory risk. Unfortunately, my data set does not allow me to actually distinguish between HFT and regular market participants. It would be of particular interest to see how HFT trading strategies change under such circumstances. I leave this for future research.

Price Discovery, Price uncertainty, and Fragmentation Besides liquidity and order book depth, there are other important factors of market quality. The information content of a price represents such an important indicator which is directly connected to market efficiency. Several scholars argue that quote driven price information on MTFs have become even more efficient and informative than on traditional exchanges (e.g., Riordan et al., 2011; Jung and Katzschner, 2012). They contradict the argumentation of many practitioners who claim that MTFs would free-ride on the price formation of traditional exchanges. Yet, an important aspect of high market quality is not only to lead in certain market quality measures but to provide high quality services during any market condition, particularly in short periods of possible intense distress.

Table 6.5 displays regression results of Regression Model II, where I concentrate on the influence of increased price uncertainty on Hasbrouck (1995) information shares.[16] The exogenous variables are the same as in Regression Model I. However, I am mainly interested in the influence of volatility on the information contribution of each single trading platform to efficient prices. The rest of the variables serve as controls. Results indicate that increased volatility leads to an increase of LSE's information shares while MTF information shares decrease. Only the LSE and Chi-X exhibit significant results in this respect. Yet, these are also the two major markets that contribute to price discovery.[17] The influence of volatility on information shares is highly significant not only for the top 1.0% of highest volatility observations but also for the 3.0% and 5.0%.

From an economic perspective, this finding may be connected to results of Regression Model I. When price uncertainty grows, the risk of being adversely selected increases over proportionally on MTFs. Market participants seem to be aware of this fact and therefore, route their orders preferably to the LSE during these periods. Informed traders usually try to conceal their superior knowledge in periods of high trading activity (Admati and Pfleiderer, 1988). Yet, if trading activity on MTFs reduces, informed traders may be forced to follow other market participants to the LSE. This in turn leads to an increase in LSE's contribution to price discovery and – vice versa – a decrease in Chi-X's price discovery.

[16] As outlined in Section 4.2.3, information shares measure where prices "move first".
[17] See also Figure 4.3.

TABLE 6.5: ***Regression Model II: Regression results.*** *I compare 69 FTSE100 stocks traded on the LSE, Chi-X, BATS, and Turquoise between January 5 to December 30, 2009. I use the regression model presented in equation 6.4 with detrended endogenuous variables and logarithmic values of trading volumes, market capitalizations, and average stock prices. I report robust standard errors following Thompson (2011), t-statistics are presented below the regression coefficients in italics. '***' denotes significance at the 1% level, '**' at the 5% level, and '*' at the 10% level.*

Panel A – IDR Dummy 1%						
	2009 Full Sample					
	High Vola(C)	Market Making	Eff. Spread(C)	Ln Vol(C)	Ln Mcap	Ln AvPr(C)
InfoShare LSE	0.0770 ***	0.0077	0.0024 *	-0.0067 *	0.0059 **	0.0039 ***
	3.07	*1.14*	*1.87*	*-1.75*	*2.28*	*3.14*
InfoShare ChiX	-0.0753 ***	0.0005	-0.0042 ***	0.0201 ***	-0.0161 ***	-0.0051 ***
	-2.70	*0.07*	*-2.71*	*4.51*	*-5.19*	*-3.66*
InfoShare BATS	0.0005	-0.0061 **	0.0012 **	-0.0079 ***	0.0061 ***	0.0012 *
	0.07	*-2.36*	*2.36*	*-4.43*	*4.49*	*1.93*
InfoShare TQ	-0.0025	-0.0022	0.0006 *	-0.0057 ***	0.0042 ***	0.0001
	-0.44	*-1.06*	*1.72*	*-4.07*	*4.00*	*0.14*

Panel A – IDR Dummy 3%						
	2009 Full Sample					
	High Vola(C)	Market Making	Eff. Spread(C)	Ln Vol(C)	Ln Mcap	Ln AvPr(C)
InfoShare LSE	0.0450 ***	0.0081	0.0021 *	-0.0078 **	0.0066 **	0.0040 ***
	3.81	*1.19*	*1.70*	*-2.10*	*2.57*	*3.24*
InfoShare ChiX	-0.0437 ***	0.0001	-0.0039 ***	0.0211 ***	-0.0167 ***	-0.0052 ***
	-3.10	*0.02*	*-2.65*	*4.85*	*-5.47*	*-3.75*
InfoShare BATS	-0.0007	-0.0061 **	0.0013 **	-0.0078 ***	0.0061 ***	0.0012 *
	-0.18	*-2.35*	*2.41*	*-4.40*	*4.47*	*1.92*
InfoShare TQ	-0.0009	-0.0022	0.0006	-0.0057 ***	0.0042 ***	0.0001
	-0.33	*-1.06*	*1.63*	*-4.00*	*3.98*	*0.14*

continued on the next page...

. . . continued from Table 6.5

Panel A – IDR Dummy 5%

	2009 Full Sample					
	High Vola(C)	Market Making	Eff. Spread(C)	Ln Vol(C)	Ln Mcap	Ln AvPr(C)
InfoShare LSE	0.0409 ***	0.0075	0.0018	-0.0086 **	0.0072 ***	0.0040 ***
	4.52	*1.13*	*1.58*	*-2.35*	*2.81*	*3.22*
InfoShare ChiX	-0.0420 ***	0.0007	-0.0035 ***	0.0221 ***	-0.0173 ***	-0.0052 ***
	-3.97	*0.09*	*-2.58*	*5.19*	*-5.75*	*-3.72*
InfoShare BATS	0.0700	-0.0061 **	0.0012	-0.0079 ***	0.0062 ***	0.0012 *
	0.27	*-2.36*	*2.35*	*-4.48*	*4.51*	*1.94*
InfoShare TQ	0.0000	-0.0022	0.0006	-0.0058 ***	0.0042 ***	0.0001
	-0.02	*-1.06*	*1.56*	*-4.04*	*3.98*	*0.16*

6.5 Conclusion

MTFs have captured a significant share of trading volume from traditional exchanges over the recent years. The main drivers for this development is their focus on high-speed trading technology and innovative fee models. This change within the European trading landscape went hand in hand with the appearance of a new trader clientele which fits perfectly to the institutional setup that MTFs provide. Speed sensitive investors, known as HFT, are today responsible for 40% to 60% of daily trading volume in European blue chip indices.[18] Through SOR technology, HFT is able to place orders on different trading venues within milliseconds in order to gain trading profits. These trading strategies connect markets instantly and further lead to a quasi multi-venue market making activity of HFT. Several scholars argue that these activities positively influence overall market quality (e.g., Menkveld, 2011b; Kirilenko et al., 2011). They also argue that MTF transaction price pressure on traditional exchanges triggers positive welfare effects for the market in general. Others claim that MTFs are in the meantime ahead in price discovery compared to traditional exchanges and that MTFs incorporate a higher degree of information based trading (e.g., Hoffmann, 2010; Riordan et al., 2011; Jung and Katzschner, 2012).

Yet, an important aspect of market quality is the provision of high quality services during any market condition, but particularly in periods of possibly intense distress. MTFs may grant these high quality services in times of severe market turmoil, but they also depend on active market participants who trade during these periods in order to keep up high market quality. Especially with regard to HFT activity, which is stronger on MTFs, questions arise whether market quality on these trading venues is reliable also in difficult market situations.

This chapter addresses the influence of increased price uncertainty and other market conditions on order routing differences of market participants between the LSE, Chi-X, BATS, and Turquoise. My results suggest that market participants prefer to trade on the LSE when price uncertainty is high. This result may stem from an over-proportional

[18] See `http://hft.thomsonreuters.com/`

adverse selection risk on MTFs during periods of high price uncertainty. Others have found that the share of informed trading is higher on MTFs and thus is the risk of being adversely selected, particularly when price uncertainty increases. Connected to this finding is my evidence that suggests a decreasing information content of MTF prices when price uncertainty increases. As market participants seem to be aware of the increased adverse selection risk on MTFs during periods of high market distress, they choose to trade over the LSE or they reduce their trading activity generally. Informed market participants may potentially follow the uninformed ones to the LSE, as my results suggest a strong increase in LSE's price discovery in periods of increased market uncertainty. I also find a significant drop in MTF trading activity on trading days which are associated with difficult market making. As HFT can choose when to provide liquidity or not, I explain this finding with a reduction of HFT market making activity – via limit order submission – as soon as market making becomes difficult and thus costly.

In general, the findings of this chapter point to the trust of market participants in the price formation process of the LSE, particularly in periods of severe distress. This trust may also be connected to a superior service provision which is not only focused on speed, but also on other important factors, e. g. , real market makers, circuit breakers, an independent market surveillance unit, etc. It shows that not all market participants are equally speed sensitive and therefore, traders may have heterogeneous preferences about speed and the location of order execution, accordingly (Pagnotta and Philippon, 2012).

Chapter 7

Conclusion

"Regulators' task has been to facilitate an appropriately balanced market structure that promotes competition among markets, while minimizing the potentially adverse effects of fragmentation [...] Given the complexity of this task, there clearly is room for reasonable disagreement as to whether the market structure at any particular time is, in fact, achieving an appropriate balance of these multiple objectives. Accordingly, [...] it is important to monitor these issues and, periodically, give the public, including the full range of investors and other market participants, an opportunity to submit their views on the matter."

U.S. Securities and Exchange Commission (2013)

Chapter Overview. This chapter of the thesis contains two sections. Section 7.1 summarizes the main findings of my empirical research. Section 7.2 provides an outlook with regard to future research questions which are connected to the fragmented European equity trading environment.

7.1 Summary

THE trading landscape of European equity markets has changed tremendously since the introduction of MiFID in November 2007. This European Directive allowed new alternative trading venues to compete for equity order flow and particularly MTFs have captured a significant share of it. Consequently, the quasi-monopoly of traditional exchanges ended and order flow and liquidity have become fragmented ever since. Along with fragmentation, questions arise about the economic effects of this regulatory change. One the one hand, there might be negative effects associated to market fragmentation, as it seems intuitive to concentrate trading as much as possible at one trading venue in order to increase the probability of order execution. Additionally, market fragmentation may decrease transparency and lead to increasing search costs for market participants. On the other hand, market participants may benefit from order flow competition as it is connected to competition in transaction fees and to the proliferation of new services that are meant to attract investors.

This thesis provides a comprehensive empirical analysis of trading venue competition in Europe's most fragmented equity market, the UK. In particular it addresses the influence of increased fragmentation and competition on market quality in FTSE 100 stocks during 2009. Tick-size order book data of the LSE, Chi-X, BATS, and Turquoise, with a total of 2.72 billion data points, reveal various interesting results with regard to market quality and the order routing behavior of market participants.

The results of Chapter 5 clearly indicate that MTFs are able to capture a significant share of trading volume and thus play an important role in UK equity trading. Their focus on low-latency technology and innovative fee models has granted them increasing trading activity of market participants. This increased competitive pressure leads to an improvement of overall market quality. Liquidity, measured by quoted and effective spreads, increases at all four trading venues along with market fragmentation during the observation period. Chapter 5 also addresses the relationship between order flow and liquidity in a multi-market intraday analysis during Q1 and Q4 of 2009. The results show that MTF intraday patterns of liquidity and trading intensity measure converge with LSE intraday patterns from Q1 to Q4. This indicates maturing market quality on MTFs over time. A direct comparison of individual intraday patterns reveals that particularly Chi-X exhibits market quality levels comparable of those of the LSE. Chapter 5 also shows that market participants prefer to trade on the LSE at market opening and closing, which are typically associated with increased price uncertainty. This points to potential changes in the order routing behavior of market participants depending on certain market situations. But increased intraday trading activity on the LSE may also be biased by market participants who need to open or close their position on a regulated market due to regulatory requirements (e. g. , mutual funds, insurance companies, etc.).

Chapter 6 elaborates on this question by studying the influence of abnormal market conditions on the order routing behavior of market particiants over time rather than intraday. The results of this chapter contradict findings of other scholars in several respects. Since the introduction of MiFID an increasing number of scholars have addressed the competitive relationship between MTFs and traditional exchanges. Many attribute mainly positive effects to this competitive relationship as for instance increased overall market quality, a higher degree of information based trading on MTFs or a greater contribution to efficient prices by MTFs.[1] However, most authors consider merely normal market conditions and exclude periods of market distress. Yet, an important attribute of a functioning market structure is to usually withstand relatively brief periods of serious stress to grant market participants high-quality services throughout all market conditions. The results of this chapter do not show that MTFs offer inferior services during such periods but they reveal another even more convincing finding that speaks in favor of the LSE market structure especially during periods of market distress. Market participants prefer trading on the traditional exchange when price uncertainty is high or when overall market liquidity is lower. This finding can most likely be attributed to increased adverse selection risk on MTFs.

Other scholars state that MTFs show a higher degree of informed trading (Hoffmann, 2010; Riordan et al., 2011; Jung and Katzschner, 2012). My results also support this

[1]Please see Chapter 3 for details.

idea, as for instance Chi-X price impacts – a measure for the information content of a trade – are comparable (or even larger in certain periods) to price impacts on the LSE. Additionally, Chi-X has captured the lead of offering the fastest quote-based price updates within all four markets. This means that tradeable quotes on Chi-X move before quotes of any other of the four competing trading venues. In line with these findings are further results, which point to a changing information contribution of the trading venues to efficient stock prices. Once price uncertainty is high, the information share of the LSE increases while MTF information shares decrease. Consequently, the LSE contributes much more to price discovery and their quotes are updated much quicker compared to MTFs in periods of distress.

Chapter 6 also reveals that MTF market shares decrease significantly on days connected to difficult market making and thus increased inventory risk. This result can be attributed to higher HFT activity on MTFs. These speed sensitive traders seem to reduce their trading activity significantly as soon as inventory control risk increases. Under normal market conditions, i.e., when overall liquidity increases and price uncertainty is low, MTFs gain market shares. They also exhibit a significant higher market share in large cap stocks which is connected to the increased liquidity levels of such stocks.

After all, this thesis reveals the importance of the fact that competing trading venues have acknowledged the particular needs of different trading clientele. MTFs have focused on technological developments or new services, such as alternative fee structures, which increased the competitive pressure on traditional exchanges and thus lead to an improvement of overall market quality. Yet this thesis shows, that investors may as well value other attributes of a market model than just the pure "need for speed". With its market model, the LSE fulfills supplementary functions and services (e.g., true market making, circuit breakers, independent market surveillance or the listing of new products). These services may be costly but they are also the reason for positively affecting investor confidence in periods of market distress and thus guarantee trading after all. Finally, MTFs have started to acknowledge that these supplementary services are important to gain investors' trust. It seems that they strive to reach the regulatory status of their traditional competitors. In May 2013, BATS Chi-X Europe announced that the

U.K. Financial Conduct Authority (FCA) approved BATS Chi-X Europe's application for *Recognised Investment Exchange* (RIE) status (BATS Chi-X Europe, 2013). This change in status will provide them access to a greater number of investors that are obligated to send client orders for stocks to an RIE or an equivalent. At the same time it is a commitment to further invest into risk management, market surveillance and other regulatory tools and resources that will raise the former MTF on a regulated market level.

7.2 Outlook

This thesis addresses important questions regarding increased fragmentation of order flow after the introduction of MiFID. Yet, the current level playing field between regulated markets and MTFs – also with a focus on HFT trading activity – leaves room for further research.

Enlargement of the level playing field of regulated markets and MTFs MTFs seem to benefit from their regulatory status that enables them to exclude several important and costly services from their market models. These services, however, play an important role and guarantee usually stable equity trading in all market situations. Future research could contribute to a re-thinking of a greater level playing field between regulated markets and MTFs. This seems adequate since MTFs have captured a significant market share and their role in financial markets with regard to price and market influence is of great importance. To study competition effects of these trading venues with a special focus on market surveillance differences or volatility interruptions seems interesting.

The role of HFT and algorithmic traders in a fragmented market environment The importance of HFT and algorithmic trading activity which currently accounts for roughly 40% to 60% of trading volume in European blue chip indices is enormous.[2] Unfortunately, this thesis could only approximate the trading activity of these market participants because a specific data set which clearly identifies these traders is unavailable. Flagged algorithmic or HFT data from trading venues or broker level data directly would allow a detailed analysis of trading strategies and market making activity of these market participants. Also the research of new safeguards for the market in the light of HFT activities seems necessary with a particular focus on the real economic benefits of HFT.

[2]See `http://hft.thomsonreuters.com/`

Secondary effects of market fragmentation on market quality Scholarly results, as well as my findings indicate an increase in overall market quality along with raising fragmentation levels. However, my analysis also highlights that this is predominately the case for normal market conditions, mainly large cap stocks, or market participants that have access to smart order routing technologies.

Besides abnormal market conditions, other secondary effects of market fragmentation have been widely neglected and may deliver interesting research insights. Firstly, the scattering of liquidity might lead to a situation where several market participants (e.g. mutual funds, investment funds) are forced to withdraw from trading in particular stocks that do not exhibit a satisfying liquidity level on the regulated market as they are traded mainly on alternative trading platforms. These market participants are regulated not to invest into stocks with insufficient liquidity levels. A common measure for satisfying liquidity levels is a stock's trading share on a regulated market.

Secondly, connected to liquidity fragmentation is the dilution of index weights of a stock. As part of an index – no matter if blue chip or small cap – it does not matter for a stock whether it is frequently traded on alternative trading platforms. Merely trading activity on the regulated market that hosts the index accounts for the calculation of the stocks index weight. This increases the risk of an index drop-out for stocks that are infrequently traded on the regulated market. Contrarily, it hinders the chances of a stock to move up the index ladder, which would be quite beneficial as it is connected with increased transparency.

Overall, there are still many promising topics to be covered and especially the updated version of MiFID will bring up new and interesting research topics once it will be implemented in 2015.

Part I

Appendix

Appendix A

Complementary Statistics & Further Information

A.1 Augmented Dickey-Fuller Tests for Stationarity

Number of lags in the Unit Root tests was selected by the AIC information criterion.

A.1.1 ADF Tests for Fragmentation Time Series

Augmented Dickey-Fuller Unit Root Tests for Fragementation time Series							
Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	1	-132.998	0.0001	-8.14	<.0001		
	2	-78.8555	<.0001	-6.25	<.0001		
	3	-55.0224	<.0001	-5.21	<.0001		
	4	-39.4289	<.0001	-4.4	<.0001		
	5	-31.7689	<.0001	-3.94	<.0001		
Single Mean	1	-2337.54	0.0001	-34.19	<.0001	584.5	0.001
	2	-1507.67	0.0001	-26.86	<.0001	360.8	0.001
	3	-1106.71	0.0001	-22.78	<.0001	259.55	0.001
	4	-820.05	0.0001	-19.55	<.0001	191.06	0.001
	5	-679.367	0.0001	-17.73	<.0001	157.12	0.001
Trend	1	-2343.28	0.0001	-34.23	<.0001	585.88	0.001
	2	-1511.69	0.0001	-26.9	<.0001	361.69	0.001
	3	-1109.81	0.0001	-22.81	<.0001	260.21	0.001
	4	-822.384	0.0001	-19.57	<.0001	191.55	0.001
	5	-681.349	0.0001	-17.75	<.0001	157.53	0.001

TABLE A.1: *ADF tests: Fragmentation time series.*

A.1.2 ADF Tests for LSE Market Share Time Series

Augmented Dickey-Fuller Unit Root Tests for LSE Market Shares							
Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	1	-47.0606	<.0001	-4.87	<.0001		
	2	-28.0457	<.0001	-3.76	0.0002		
	3	-19.6902	0.0019	-3.16	0.0016		
	4	-14.3063	0.0086	-2.71	0.0067		
	5	-11.6205	0.0179	-2.45	0.0141		
Single Mean	1	-2337.54	0.0001	-34.19	<.0001	584.5	0.001
	2	-1507.67	0.0001	-26.86	<.0001	360.8	0.001
	3	-1106.71	0.0001	-22.78	<.0001	259.55	0.001
	4	-820.05	0.0001	-19.55	<.0001	191.06	0.001
	5	-679.367	0.0001	-17.73	<.0001	157.12	0.001
Trend	1	-2343.28	0.0001	-34.23	<.0001	585.88	0.001
	2	-1511.69	0.0001	-26.9	<.0001	361.69	0.001
	3	-1109.81	0.0001	-22.81	<.0001	260.21	0.001
	4	-822.384	0.0001	-19.57	<.0001	191.55	0.001
	5	-681.349	0.0001	-17.75	<.0001	157.53	0.001

TABLE A.2: *ADF tests: LSE market shares.*

A.1.3 ADF Tests for CHI-X Market Share Time Series

Augmented Dickey-Fuller Unit Root Tests for Chi-X Market Shares							
Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	1	-161.182	0.0001	-8.96	<.0001		
	2	-95.4744	<.0001	-6.88	<.0001		
	3	-67.4084	<.0001	-5.77	<.0001		
	4	-50.4709	<.0001	-4.98	<.0001		
	5	-40.3141	<.0001	-4.44	<.0001		
Single Mean	1	-2413.68	0.0001	-34.75	<.0001	603.62	0.001
	2	-1557.02	0.0001	-27.28	<.0001	372.08	0.001
	3	-1158.57	0.0001	-23.28	<.0001	270.87	0.001
	4	-900.832	0.0001	-20.41	<.0001	208.34	0.001
	5	-740.97	0.0001	-18.44	<.0001	170.06	0.001
Trend	1	-2424.07	0.0001	-34.82	<.0001	606.15	0.001
	2	-1564.33	0.0001	-27.34	<.0001	373.72	0.001
	3	-1164.32	0.0001	-23.33	<.0001	272.12	0.001
	4	-905.446	0.0001	-20.46	<.0001	209.32	0.001
	5	-744.876	0.0001	-18.49	<.0001	170.88	0.001

TABLE A.3: *ADF tests: Chi-X market shares.*

A.1.4 ADF Tests for BATS Market Share Time Series

Augmented Dickey-Fuller Unit Root Tests for BATS Market Shares							
Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	1	-483.372	0.0001	-15.53	<.0001		
	2	-293.832	0.0001	-12.04	<.0001		
	3	-202.342	0.0001	-9.97	<.0001		
	4	-160.119	0.0001	-8.85	<.0001		
	5	-138.695	0.0001	-8.22	<.0001		
Single Mean	1	-1773.45	0.0001	-29.78	<.0001	443.31	0.001
	2	-1132.76	0.0001	-23.4	<.0001	273.89	0.001
	3	-802.5	0.0001	-19.56	<.0001	191.36	0.001
	4	-649.388	0.0001	-17.51	<.0001	153.38	0.001
	5	-574.154	0.0001	-16.39	<.0001	134.29	0.001
Trend	1	-1774.02	0.0001	-29.78	<.0001	443.42	0.001
	2	-1133.14	0.0001	-23.41	<.0001	273.96	0.001
	3	-802.784	0.0001	-19.57	<.0001	191.42	0.001
	4	-649.619	0.0001	-17.52	<.0001	153.42	0.001
	5	-574.36	0.0001	-16.39	<.0001	134.33	0.001

TABLE A.4: *ADF tests: BATS market shares.*

A.1.5 ADF Tests for Turquoise Market Share Time Series

Augmented Dickey-Fuller Unit Root Tests for Turquoise Market Shares							
Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	1	-519.641	0.0001	-16.12	<.0001		
	2	-323.28	0.0001	-12.66	<.0001		
	3	-225.94	0.0001	-10.56	<.0001		
	4	-159.617	0.0001	-8.87	<.0001		
	5	-131.196	0.0001	-8.04	<.0001		
Single Mean	1	-3505.14	0.0001	-41.86	<.0001	876.11	0.001
	2	-2450.74	0.0001	-33.79	<.0001	570.94	0.001
	3	-1838.65	0.0001	-28.78	<.0001	414.22	0.001
	4	-1351.6	0.0001	-24.55	<.0001	301.39	0.001
	5	-1154.85	0.0001	-22.52	<.0001	253.67	0.001
Trend	1	-3505.27	0.0001	-41.86	<.0001	876.1	0.001
	2	-2450.85	0.0001	-33.79	<.0001	570.93	0.001
	3	-1838.75	0.0001	-28.78	<.0001	414.21	0.001
	4	-1351.67	0.0001	-24.55	<.0001	301.4	0.001
	5	-1154.92	0.0001	-22.52	<.0001	253.67	0.001

TABLE A.5: *ADF tests: Turquoise market hares.*

A.2 Selected Companies

TABLE A.6: ***Company sample list of FTSE 100 constituents.*** *This table contains all stocks that fulfill the filter criteria outlined in Section 4.1. The list contains the company names, their official ticker symbol, their average daily market capitalization as well as the average daily trading volume on all four trading venues.*

Name	Ticker Symbol	MCAP (mGBP)	Trading Volume (kGBP)
HSBC HOLDINGS	HSBA	95233.18	64365.20
BP	BP	96693.11	53679.91
BHP BILLITON	BLT	93968.62	51553.35
RIO TINTO	RIO	48215.07	49588.63
VODAFONE GROUP	VOD	67639.27	42724.11
BARCLAYS	BARC	26385.62	39438.36
ANGLO AMERICAN	AAL	23711.60	32729.43
GLAXOSMITHKLINE	GSK	60249.21	31334.97
XSTRATA	XTA	20076.37	30763.92
ASTRAZENECA	AZN	38382.84	29372.62
ROYAL DUTCH SHELL B	RDSb	103763.27	24853.99
BG GROUP	BG	35537.24	22192.08
STANDARD CHARTERED	STAN	23913.67	21476.55
BRIT AM TOBACCO	BATS	36049.98	21036.13
ROYAL DUTCH SHELL A	RDSa	103763.27	19412.70
TESCO	TSCO	29212.67	18703.96
LLOYDS BANKING GROUP	LLOY	19410.61	18404.69
DIAGEO	DGE	22781.75	15608.92
UNILEVER	ULVR	47860.66	14991.42
RECKIT BENCKISER GROUP	RB	20214.32	13609.18
BAE SYSTEMS	BAES	12151.11	13080.46
IMPERIAL TOBACCO	IMT	17404.02	12965.21
PRUDENTIAL	PRU	11533.06	12470.73
SABMILLER PLC	SAB	20744.70	11095.89
ROYAL BANK OF SCOTLAND	RBS	19816.78	10954.66
NATIONAL GRID	NG	14512.22	10007.88
AVIVA	AV	9456.02	9955.95
CADBURY	CBRY	8526.47	9770.82
CENTRICA	CNA	12570.70	9238.03
REED ELSEVIER	REL	5566.21	9038.19
WPP PLC	WPP	5911.84	8741.97
BT GROUP	BT	8855.64	8547.76
MARKS & SPENCER GROUP	MKS	5032.95	8355.31
VEDANTA RESOURCES	VED	4079.08	8341.78
ROLLS ROYCE	RR	7178.85	7834.07

continued on the next page…

...continued from Table A.6

Name	Ticker Symbol	MCAP (mGBP)	Trading Volume (kGBP)
COMPASS GROUP	CPG	6532.35	7786.64
SCOTTISH & SOUTHERN ENERGY	SSE	10363.90	7476.43
TULLOW OIL	TLW	7776.81	7211.82
PEARSON	PSON	5788.18	7208.44
MORRISON SUPERMARKETS	MRW	6947.64	7050.38
KAZAKHMYS	KAZ	4050.48	6996.84
BRITISH SKY BROADCASTING	BSY	8712.18	6960.20
NEXT	NXT	3102.30	6921.55
KINGFISHER	KGF	4447.44	6836.32
BRITISH LAND COMPANY	BLND	3467.37	6543.83
ANTOFAGASTA	ANTO	6539.71	6521.49
LAND SECURITIES GROUP	LAND	4032.81	6282.55
MAN GROUP	EMG	4544.06	6225.73
CARNIVAL	CCL	14231.54	5656.88
SAINSBURY(J)	SBRY	5814.70	5493.62
INTERNATIONAL POWER	IPR	3934.73	5341.32
BRITISH AIRWAYS	BAY	1936.66	4997.90
CABLE & WIRELESS	CW	3645.82	4711.40
SMITH & NEPHEW	SN	4451.38	4691.37
LEGAL & GENERAL	LGEN	3787.24	4603.33
AUTONOMY CORPORATION	AUTN	3198.89	4587.83
UNITED UTILITIES GROUP	UU	3370.91	4150.12
EXPERIAN	EXPN	5019.49	4051.30
OLD MUTUAL	OML	4251.65	3951.90
RSA INSURANCE GROUP	RSA	4259.86	3681.97
INTERCONTINENTAL HOTELS	IHG	1948.42	3479.64
CAPITA GROUP	CPI	4382.56	3419.63
HAMMERSON	HMSO	2209.14	3415.13
SMITHS GROUP	SMIN	3186.34	3304.18
REXAM PLC	REX	2079.48	3263.85
SEVERN TRENT	SVT	2459.34	3228.72
JOHNSON MATTHEY	JMAT	2709.00	2612.40
ICAP PLC	IAP	2478.77	2494.10
SAGE GROUP	SGE	2580.82	2483.41

A.3 Sample of Trade and Quote Data

TABLE A.8: ***Raw trade and quote data - sample LSE.*** *This table presents raw TAQ data from the LSE order book retrieved from Thomson Reuters Tick History archive. The stock in this sample is «Experian».*

#RIC	Date[G]	Time[G]	GMT Offset	Type	Price	Volume	Bid Price	Bid Size	Ask Price	Ask Size
EXPN.L	08/26/09	08:54:53.96	1	Quote			524.5	3700	525	19422
EXPN.L	08/26/09	08:54:53.96	1	Quote			524.5	3700	525	20401
EXPN.L	08/26/09	08:54:59.12	1	Quote			524.5	4270	525	20401
EXPN.L	08/26/09	08:55:05.59	1	Trade	525	10				
EXPN.L	08/26/09	08:55:05.59	1	Quote			524.5	4270	525	20391
EXPN.L	08/26/09	08:55:54.96	1	Quote			524.5	4782	525	20391
EXPN.L	08/26/09	08:56:00.97	1	Quote			524.5	5322	525	20391
EXPN.L	08/26/09	08:56:12.71	1	Quote			524.5	5322	525	22359
EXPN.L	08/26/09	08:56:23.45	1	Quote			524.5	6822	525	22359
EXPN.L	08/26/09	08:56:58.45	1	Quote			524.5	7222	525	22359
EXPN.L	08/26/09	08:57:28.15	1	Trade	524.5	669				
EXPN.L	08/26/09	08:57:28.15	1	Quote			524.5	6553	525	22359
EXPN.L	08/26/09	08:57:36.53	1	Quote			524.5	7085	525	22359
EXPN.L	08/26/09	08:58:02.36	1	Quote			524.5	8371	525	22359
EXPN.L	08/26/09	08:58:04.26	1	Quote			524.5	7085	525	22359
EXPN.L	08/26/09	08:58:14.77	1	Quote			524.5	7478	525	22359
EXPN.L	08/26/09	08:59:06.41	1	Quote			524.5	7478	525	23746
EXPN.L	08/26/09	08:59:24.01	1	Quote			524.5	6908	525	23746
EXPN.L	08/26/09	08:59:25.97	1	Quote			524.5	7958	525	23746
EXPN.L	08/26/09	08:59:28.23	1	Quote			524.5	11451	525	23746
EXPN.L	08/26/09	08:59:32.14	1	Quote			524.5	11451	525	21778
EXPN.L	08/26/09	08:59:32.31	1	Trade	524.5	1331				
EXPN.L	08/26/09	08:59:32.31	1	Trade	524.5	1700				
EXPN.L	08/26/09	08:59:32.31	1	Trade	524.5	512				
EXPN.L	08/26/09	08:59:32.33	1	Trade	524.5	540				
EXPN.L	08/26/09	08:59:32.33	1	Trade	524.5	1500				
EXPN.L	08/26/09	08:59:32.33	1	Trade	524.5	400				
EXPN.L	08/26/09	08:59:32.33	1	Trade	524.5	532				
EXPN.L	08/26/09	08:59:32.33	1	Trade	524.5	393				
EXPN.L	08/26/09	08:59:32.33	1	Trade	524.5	1050				
EXPN.L	08/26/09	08:59:32.33	1	Trade	524.5	1202				
EXPN.L	08/26/09	08:59:32.33	1	Quote			524.5	2291	525	21778

Appendix B

List of Abbreviations

ADF	Augmented Dickey Fuller Test	62
AEX	Amsterdam Exchange Index	27
AIC	Aikake Information Criterion	62
AMEX	American Stock Exchange	42
AT	Automated Trading	114
CAC	Cotation Assistée en Continu	27
CESR	Committee of European Securities Regulators	15
CSE	Cincinnati Stock Exchange	41
DAX	Deutscher Aktien Index	27
EEA	European Economic Area	15
ETF	Exchange Traded Fund	42
EU	European Union	2
FCA	Financial Conduct Authority	146
FSAP	Financial Services Action Plan	2
FTSE	Financial Times Stock Exchange	3
HFT	High Frequency Trading	5
ISD	Investment Services Directive	2
KIT	Karlsruhe Institute of Technology	57
LSE	London Stock Exchange	2
MiFID	Markets in Financial Instruments Directive	2
MTF	Multilateral Trading Facilities	2
NASDAQ	National Association of Securities Dealers Automated Quotations	23
NYSE	New York Stock Exchange	40
OLS	Ordinary Least Squared	123
RIC	Reuters Instrument Code	57
RIE	Recognised Investment Exchange	146
SEAQ	Stock Exchange Automated Quotation system	23
SETS	Stock Exchange Trading System	24
SI	Systematic Internalizer	2
SOR	Smart Order Routing Technologies	4
VFTSE	FTSE 100 Volatility Index	124
VMA	Vector Moving Average	69

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